recycling

Review

The Application of Artificial Intelligence in the Effective Battery Life Cycle in the Closed Circular Economy Model—A Perspective

Agnieszka Pregowska [1], Magdalena Osial [1] and Weronika Urbańska [2,*]

[1] Institute of Fundamental Technological Research, Polish Academy of Sciences, Pawinskiego 5B Street, 02-106 Warsaw, Poland
[2] Faculty of Environmental Engineering, Wrocław University of Science and Technology, Wybrzeże Wyspiańskiego 27, 50-370 Wroclaw, Poland
* Correspondence: weronika.urbanska@pwr.edu.pl

Abstract: Global pollution of the environment is one of the most challenging environmental problems. Electronic-based population and anthropogenic activity are the main reasons for dramatically increasing the scale of waste generation, particularly battery waste. Improper battery waste disposal causes harmful environmental effects. Due to the release of heavy metals, battery waste affects ecosystems and health. We are faced with the challenge of effective battery waste management, especially recycling, to prevent the depletion of natural resources and maintain ecological balance. Artificial Intelligence (AI) is practically present in all areas of our lives. It enables the reduction of the costs associated with various types of research, increases automation, and accelerates productivity. This paper reviews the representative research progress of effective Artificial Intelligence-based battery waste management in the context of sustainable development, in particular, the analysis of current trends, algorithm accuracy, and data availability. Finally, the future lines of research and development directions of human-oriented Artificial Intelligence applications both in the battery production process and in battery waste management are discussed.

Keywords: battery waste; waste management; artificial intelligence; machine learning; genetic programming; end-of-life

check for updates

Citation: Pregowska, A.; Osial, M.; Urbańska, W. The Application of Artificial Intelligence in the Effective Battery Life Cycle in the Closed Circular Economy Model—A Perspective. *Recycling* **2022**, *7*, 81. https://doi.org/10.3390/recycling7060081

Academic Editor: Anna Klemettinen

Received: 22 September 2022
Accepted: 4 November 2022
Published: 7 November 2022

1. Introduction

The growing standard of living, inextricably linked with the growing demand for electronics, is driving the market for the recycling of spent batteries. The global battery recycling market has been valued at USD 10.21 billion in 2021 and is projected to reach USD 18.96 billion by 2030, with a compound annual growth rate (CAGR) of 7.12% over the forecast period. In the case of lithium-ion batteries (LIBs), the market has been valued at USD 6.55 billion by 2028, with a CAGR of 18.5% over the forecast period [1]. The battery market has rapidly grown, where only in 2019, around 205,000 tons of portable batteries and accumulators were placed on the market in the EU. The production of electric vehicles (EVs) is also increasing and, consequently, the number of batteries produced. Another issue contributing to this is that the battery used in an electric car, which has lost 20 percent of its capacity, is considered to be used up. Recalled EV batteries pose a significant threat to the environment because they contain heavy metals in many cathode materials and toxic and corrosive electrolytes [2]. Among them, cobalt accounts for 60 percent of the cost of cathodes [3]. At the same time, approximately 100,000 tons of battery waste were collected and recognized as recyclable. It also turned out that the collection of used portable batteries and accumulators is lower than the sale [4]. The rules for monitoring battery waste, taking into account goals of waste collection and the effectiveness of recycling according to the types of waste, were included in Directive 2006/66/EC on portable batteries and accumulators, and the Commission Regulation (EU) No. 493/2012 divided them into three target groups: lead-acid batteries and accumulators, nickel-cadmium batteries and accumulators, and other batteries and accumulators. Nickel-cadmium batteries are withdrawn from circulation because of cadmium toxicity [3].

The rapid growth of battery production and usage will cause waste and disposal-related issues in the next few years as these batteries reach end-of-life. Moreover, it also causes the depletion of natural mineral resources. Thus, effective battery reuse and recycling procedures are highly important because they contain metals of critical importance [5,6]. The recycling of batteries causes the return of valuable materials, including lead, lithium, nickel, cadmium, and copper [7], back to the value chain, partially easing the need to extract new resources. Moreover, recovering metals from batteries reduces the burden on landfills, the burden on the environment, and the negative impact on human health. The critical material's recirculation also leads to a reduction of the ecological CO_2 footprint, which is connected with battery cell production and may provide CO_2-neutral battery cell production [8–10]. Improper battery waste disposal causes harmful effects on human and animal health, as well as the environment, as they contain a huge number of heavy metals [11]. These waste compounds contaminate water, soil, and vegetation.

Another economic issue is related to the fact that the chemicals that are used in the production of batteries are sourced from the Congo (more than half of the cobalt), Australia and Chile (80 percent of lithium), and China (80 percent of graphite) [12]. The concentration of raw materials in these places may affect their unstable supplies to enterprises producing batteries and accumulators in other parts of the world. Thus, the unsustainable production of these strategic materials is a serious threat to the electronics industry. In addition, they are hazardous materials for transport due to their thermal and electrical instability, which translates into high transport costs. The possibility of LIB recycling provides an opportunity to avoid these issues.

In this paper, we overview the existing management systems for battery waste, including their reuse and recycling, emphasizing the use of Artificial Intelligence in the service of the natural environment. We present different technologies, such as pyrometallurgical, hydrometallurgical, and direct recycling methods, which are used in processing battery waste, taking into account the current status of LIB recycling, algorithm accuracy, and data availability, as well as the analysis of current trends and economic challenges.

2. Materials and Methods

The review methodology was based on the PRISMA Statement [13] and its extensions: PRISMA-S [14,15], as well as our personal experience. We considered recent publications, reports, protocols, and review papers from the Scopus and Web of Science databases. The keywords: "battery waste" and "smart" were used; as a result, we obtained: 245 documents, including 93 research papers, 105 conference papers, 28 conference reviews, five book chapters, one book, one letter, one editorial, one short survey, and 11 reviews in the Scopus database, and 173 documents, including 15 review articles, in the Web of Science database. Records that were duplicated in both databases, records with irrelevant titles or/and abstracts, as well as records with no AI aspects, and no ecological aspects were omitted from the analysis. The selection process was done according to the context of battery waste management and/or the use of Artificial Intelligence, in particular, Machine Learning, taking into account keywords. Finally, 139 documents were taken into account.

3. Artificial Intelligence in Battery Production and Monitoring

Battery production is one of the components of sustainable development, including reduction, clean energy, and economic development. An important role in battery production is played by cost [16]. The chemical and physical characteristics of batteries can be estimated. Optimizing the battery manufacturing process is complex (multi-criteria) and costly. It includes the optimization of factors such as, for example, electrode and slurry formulation, choices of additives and solvents, time and speed of premixing powders and slurries, coating speed and comma spacing, and time and evaporation temperature. Here, methods based on Artificial Intelligence (AI), in particular, Machine Learning (ML), can significantly simplify this process and reduce its cost while they are operating on multidimensional data sets [17]. The first important issue is to collect a large amount of reliable data on which the algorithms can perform the optimization. Incorrect assumptions and unreliable data will lead to unreliable results. Some guidance on designing suitable AI-based methods is applied to estimate the state of battery charge [18,19] and predict the battery life cycle [20,21], or LIB electrode manufacturing [22].

The State of Charge (SOC) depends on several factors, such as temperature, ageing, cell unbalancing, hysteresis characteristics, self-discharge, and charge/discharge rate. It plays an important role in predicting EVs' driving race and optimal charge control, which are crucial in reducing the carbon footprint. It can be estimated using various methods based on Artificial Intelligence, but each disadvantage is the accuracy and availability of data. The estimation of SOC requires applying the algorithm to describe the battery's remaining capacity, which was described in the study [19]. In the paper [23], a simple deep neural network combined with a Kalman filter was used to estimate the SOC of the battery. In [24], the fuzzy logic methodology was used for this purpose, which analyzed the data coming from impedance spectroscopy and/or coulomb counting techniques. A genetic algorithm was used to evaluate the various types of batteries [25,26]. Genetic algorithms provide less estimation error (5 times smaller) compared to fuzzy logic ones. The support vector machine (SVM) was used to establish the relationship of the SOC to the Ni-MH battery's voltage, current, and temperature [27]. Thus, the paper [18] proposed a recurrent neural network (RNN) with long short-term memory (LSTM) for the estimation of SOC in the case of LIB. The algorithm was based on measured voltage, current, and temperature. In [28], the dependence on ambient temperatures is included. In turn, in the study [29], convolutional neural networks (CNN) and RNN were used to predict. This approach enables the prediction of SOC with a maximum mean average error under 1% and a maximum root mean square error under 2%, based on discharge profiles. It provides a reasonable estimation of nonlinear relationships between SOC and measurable variables. Recently, hybrid methodologies to estimate SOC were investigated in the study [30]. In work [31], an adaptive extended Kalman filter was proposed. Thus, hybrid techniques have the potential to multiply the advantages of individual components and thus enable a more accurate SOC estimation.

On the other hand, the study [20] shows that Machine Learning-based techniques can predict the battery life cycle with a 4.9 percent test error using the first five cycles, considering the evolution of the discharge voltage courage. In the paper [2], the cognitive digital twin batteries' design and development were shown. This Artificial Intelligence-based digital creation enables research to optimize the entire life cycle of a battery. In [20], cycle life prediction models were proposed. As input data the cycle lives of batteries ranging from 150 to 2300 using 72 different fast-charging conditions have served. In research [22], Artificial Intelligence-based tools, in particular based on a decision tree, deep neural network, and SVM to predict correlations between LIB properties and manufacturing parameters, were proposed. It took into account the characteristics of the electrode, namely the active material mass loading and porosity. It turned out that SVM links high accuracy of prediction (above 90 percent) with the possibility of graphical analysis of the results. A huge effort has been made to understand and experimentally validate the batteries, which are working with constant current, voltage, and temperature, while there is still a gap in the case of the batteries, which are working in severe, hot, wet, and rainy conditions. Here, the surrogate battery models can be helpful, and they can be used as an input dataset to the battery optimization process [32]. Thus, Artificial Intelligence can help increase the sustainability of batteries.

Artificial Intelligence can also be applied as an effective tool for the analysis of the material characteristics of battery [33] and the LIB failure mode [34]. In the study [33], as a training set, public battery cycling data, which contains 124 $LiFePO_4$/graphite cells being cycled to end-of-life [31], was used. It turned out that to predict the battery properties with high accuracy, only single-cycle data are needed. The interesting solution for evaluating the residual energy of lithium-ion batteries (LIBs) based on Artificial Intelligence, in particular genetic programming, was presented in the paper [35]. The quantitative results determined the relationship between stress and capacity and can provide an optimized recycling strategy for batteries applied to electric vehicles, which is extremely important, while current generations of batteries link active materials with high energy densities with highly inflammable electrolytes.

In the paper [36], the dependence between the properties of the anode and cathode, manufacturing control parameters, the intermediate product characteristics, and the final cell performance with Machine Learning techniques were investigated. The Gradient Boosted Decision Trees (GBT) and random forest were applied to predict positive and negative electrodes as well as characteristics of the half-cell. As input data, a comma bar gap, coating speed, and coating ratio have been used. It turned out that the electrodes, including mass loading and thickness, can be predicted with an accuracy of 93.48 percent and the cell capacity with an accuracy of 91.75 percent.

4. Artificial Intelligence in Waste Management, Including Battery Waste Management Systems

Artificial Intelligence-based algorithms can solve various issues of information processing, including pattern recognition, classification, clustering, dimensionality reduction, image recognition, natural language processing, and predictive analysis. Recently, Artificial Intelligence was also applied in waste management [37,38], providing the opportunity to link waste management, joint supervision and collection process, and safety.

Another important issue in waste management is connected with the efficiency of the cleaning process, while Artificial Intelligence can also support waste collection schedules. The intelligent trash cans can send data, such as the presence and volume occupied by garbage, using the Internet. In the paper [39], a waste collection system based on location intelligence and applying graph optimization algorithms as a part of Smart City (Copenhagen, Denmark) was proposed. The proposed solution returns the data concerning trash level collected by the embedded sensors to the server over the Internet, which optimizes the collection routes and sends this information to workers. In this study, input data were: waste level of trashcans, which come from 3046 trashcans, and available open data about the city of Copenhagen, Denmark. On their basis, the optimal schedule of waste collection from individual places is determined, taking into account the optimization of the driving distance of the daily routes based on the Shortest Path Spanning Tree (SPST) to calculate the minimum driving distance between points and a genetic algorithm to predict the minimal driving distance between the points, is determined.

The identification, localization, and size determination of waste are based on image recognition techniques. In the study [40], based on images, the determination of the location and the degree of filling of the containers with the use of four Laws Masks and a set of support vector machine (SVM) classifiers with 99.8 percent accuracy was proposed. The containers were classified into three groups, i.e., empty, partially full, or full. The assignment to a particular group determined the garbage collection schedule. Input data were in the form of pictures of bins and the nearest neighborhoods (800 $\times$ 600 pixels), including 60 rotated and 160 unrotated. As a training set, unrotated pictures were used, while during testing of the solution proposed, both unrotated and rotated pictures were. All pictures were converted into grayscale and subjected to the automatic edge detection procedure. The bin position of the image was detected with Hough line detection and cross-correlation. It turned out that the algorithms proposed are robust against bin shift and rotation. In the research [41], the classification of electrical and electronic waste from trash pictures using the deep learning convolutional neural network (CNN) was presented. The proposed solution provides efficiency of 97 percent. As input data, pictures of refrigerators, washing machines, and television sets (three classes) in the RDG format (128 × 128 pixels) were taken. The training set includes 160 pictures (60 for each class), while the testing set includes 30 pictures (10 for each class). The pictures of waste are sent to the server, where they are subjected to the object recognition procedure. Once the waste is identified and located, waste collectors can plan for efficient collection. The systems can recognize three categories of e-waste, namely: refrigerators, washing machines, and monitors or TV sets. In the paper [42], convolutional neural networks were used to identify hazardous recyclable materials, such as batteries, syringes, and nonhazardous waste, with an accuracy of 90 percent. Datasets, including three categories (i.e., batteries, syringes, and nonhazardous waste), in the number of pictures taken in front of a white background with moderate lighting (512 × 384 pixels): 23, 91, and 1984, respectively. Artificial Intelligence-based algorithms are also involved in trash control in institutions, for example, universities [38]. This system combines linear regression (LR) with Machine Learning techniques. Dijkstra's algorithm optimizes the path for waste collection based on historical data. It operates on data containing information about the current state of filling the bin, i.e., the level of waste and bin position. The pictures were collected for 4 months during the academic year.

Thus, waste management can be treated as a multi-hierarchical clustering problem. In the paper [43], the concept of an AI-based classification of medical waste, e-waste, and toxic atmosphere pollutants, taking into account real-time indicator conditions such as daily waste and strain, was proposed. This system contains three modules: the input module (responsible for defining the essential trash characteristics), the second level module (description of the toxic patterns), and the community module. The general idea of the system is derived from LCA, MCA, and Extended Producer Responsibility. It enables e-waste tracking, taking into account the safety of the whole process. In the case of the application of Artificial Intelligence, this can reduce the duration of the assessment process by at least 35 percent.

Waste management, in particular solid waste, is an important issue, taking into account the negative impact on human health and the environment [44,45]. For an efficient waste management system, Artificial Intelligence has great potential [46]. According to the research analysis presented in [47–49], the reduction of waste through recycling helps to achieve a circular economy. The prediction of an accurate waste amount, mass, and type is crucial in waste management. Thus, in the paper [50], the convolution neural network was used to predict the waste mass. In the study [51], artificial neural networks and the Machine Learning framework (MLDPAF) were applied to the effective planning of waste management, including the prediction of waste amount and effectiveness of waste collection. The research [51] shows an attempt at waste management on an academic campus. In turn, in the paper [52], the concept of an effective construction waste management system was proposed.

Another issue connected with waste management strategies is waste amount prediction. In the study [53], multi-layer perceptron artificial neural networks (MLP-ANN) were used for the verification of annual waste production, including municipal, commercial, construction, and demolition waste. For the forecast, the data, which contain solid waste datasets deposited at Askar Landfill in Bahrain between 1997 and 2016, were used. It turned out that artificial neural networks enabled the estimation of the future-proof generation of different types of waste with high accuracy. In the paper [54], the comparison of different artificial neural networks, i.e., adaptive neuro-fuzzy inference systems, discrete wavelet theory artificial neural networks (DW-ANN), discrete wavelet theory–adaptive neuro-fuzzy inference systems (DWT-ANFIS), and genetic algorithms, for the amount of waste prediction has been made. This study covered two data streams, namely, data that come from governmental, semi-governmental, and private publications from the period of 1993–2011 and data that come from field surveys. It turned out that the most accurate forecast was delivered by a genetic algorithm. In the study [55], four options were used to estimate the ability of intelligent systems algorithms to predict monthly amounts of waste generated—support vector machines (SVM), adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANN) and k-nearest neighbors (kNN). It has been shown that AI can be successfully used to estimate the amount of generated waste, and the best results were obtained for the ANFIS (most accurate peak forecasts) and kNN (monthly average waste prediction) systems. The medical waste generation rate was estimated in [56] based on multiple linear regression, artificial neural networks, fuzzy logic–artificial neural networks, support vector regression, least squares support vector regression, and fuzzy logic–support vector regression. It turned out that in the case of hospital solid waste, the higher accuracy was provided by fuzzy logic–support vector regression.

5. Artificial Intelligence in the Waste Sorting

Waste sorting, i.e., the process of separating waste into different types, plays a crucial role in the closed circular economy model [57]. The available sorting methods can be divided into two groups: manual sorting and automated/mechanical sorting, with the application of robotic technology or a combination of these two types [58]. In the case of solid waste, the manual approach prevails [59]. To provide an automatic waste sorting system based only on pictures of waste in [60], convolution neural networks and support vector machines were applied. The system classified waste into three groups, namely plastic, paper, and metal. It operates on colored images in png format (256 × 256 pixels). It turned out that support vector machines provided higher efficiency than convolution neural networks. An interesting approach was proposed in the paper [61], placing RFID tags on packages that would enable the identification and classification of individual plastic packages, for example, using Artificial Intelligence. The recycling robot ZRR2 from ZenRobotics in Finland [62] was the first attempt to apply such a solution in practice [63]. It has built-in computer vision and deep learning algorithms. The robot enables the automatic separation of selected waste from solid construction and demolition waste. In the study [64], the ZRR robot was applied to the sorting of municipal household waste streams. In this case, the main limitation in the application of the system is the protection of personal data from households. In turn, for the already collected waste the identification to sort them into two groups, i.e., glassware and plastics, based on a convolution neural network was proposed in the paper [65]. The input data was gathered with an RGB camera, i.e., 103 pictures of waste (50 glassware, 53 plastics). To increase the amount of data, image enhancement was done to the training set. After identification, the gripper sorting robot separated the waste into two groups. In the study [66], an Artificial Intelligence-based, especially hierarchical deep learning, algorithm was applied to waste detection and classification in food trays. As input, the Labeled Waste in the Wild dataset was used, which contains 1002 RGB pictures of used food trays (3456 × 4608 pixels) that have been taken with several different smartphones. Some of the objects shown in the photos were not wasted. These pictures were used to label the shape and material of the visible waste. In the paper [67], to distinguish nails and screws in construction waste, a region-based convolutional neural network was applied. The COVID-19 pandemic also revealed the need for automatic sorting of medical waste, including polyethene terephthalate (PET) waste from the pandemic period. In the study [68], the support vector machine with an accuracy of 96.5 percent was proposed for this purpose.

Since improper segregation of biomedical waste causes health hazards, the application of Artificial Intelligence to their disposal and recycling seems to be a reasonable solution [69]. One of the directions is smart bins [70]. In the first step, they have the possibility to identify and segregate waste. Next, they choose a suitable disposal method and transfer it to recycling. In turn, Abeygunawardhana et al. [71] presented the concept of such smart bins for sorting the most common solid waste—metal, glass, and plastic. Their proposal uses the convolutional neural network (CNN) system—waste is segregated using image processing and machine learning algorithms. The use of CNN made it possible to obtain a 70 percent validation accuracy with a loss of 0.03.

6. Artificial Intelligence in Battery Waste Recycling

Effective and environmentally friendly waste management is one of the biggest problems in the whole world. Waste processing and recovery are crucial elements in waste management systems [72,73]. One of the crucial parts of battery waste management is the recycling process [74]. Lithium-ion batteries can be recycled using various methods, including pyrometallurgical, hydrometallurgical, and biological recycling to recover valuable metals [75–77]. Figure 1 shows a schematic diagram of the management system and waste recovery methods for the current batteries (including LiBs).

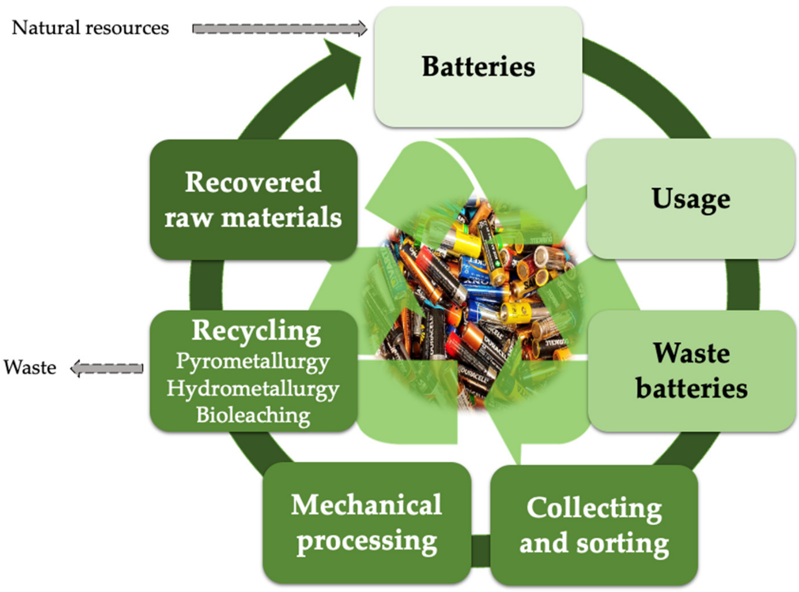

Figure 1. The closed-loop system in batteries and their waste management.

The pyrometallurgical approach is based on the high-temperature treatment of the battery waste in a wide range of temperatures in the furnace. During this process, the decomposition of organic materials occurs, and new alloys are formed [78]. It is an effective way to recover metals such as cobalt, nickel, and copper, while lithium, manganese, and aluminum get into slag or kiln dust. As a consequence, lithium, manganese, and aluminum can be extracted with a large financial outlay in another process. During this process, semi-finished products are produced, which, to be reusable, have to be subjected to further purification. The huge disadvantage of the pyrometallurgical process is the small number of recyclable materials and low efficiency in the case of low concentrations of recyclable materials [78,79]. The pyrometallurgical process is quite simple and does not cause any operational problems, but it causes air pollution and requires a lot of energy [80]. Moreover, there is no need for sorting or reduction of battery size [81,82]. Low energy consumption and high recycling efficiency are the hallmarks of hydrometallurgy processes [83]. Hydrometallurgical methods of recovering metals from used batteries most often mean acid leaching, which is based mainly on the application of strong inorganic acids and reduction. For example, refs. [84–86] proposed the application of sulphuric acid and hydrogen peroxide as leaching agents due to the fact that the use of strong inorganic reagents is associated with technological problems, such as corrosion and rapid destruction of equipment, the emission of toxic vapors, and the danger of working with strong chemicals, currently. The interest of scientists is focused on the possibility of applying organic acids (e.g., acetic, citric, and DL-malic acids) in the leaching process of spent batteries [87,88]. In addition, an up-and-coming alternative to the pyrometallurgical and hydrometallurgical recovery of metals from waste batteries is the bioleaching process using microorganisms such as bacteria and fungi [89,90]. Biological methods of metal recovery allow for the reduction of the formation of secondary pollutants (including no toxic gas emissions) and, at the same time, are characterized by high efficiency, safety, and the relatively low costs of the process. However, the duration of the reaction in most cases is longer than for the acid leaching with the use of chemical reagents [91,92].

Since the recycling of metals from battery waste is a complex task, its efficiency can be improved by the application of various prediction methods, including Artificial Intelligence [93]. In the paper [94], the Machine Learning approach, including linear regression, random forest regression, AdaBoost regression, gradient boosting regression, and XG boost regression, to optimize the metal recovery of Zn and Mn from battery waste was proposed. As input, data on energy substrate concentration, pH control of bioleaching media, incubating temperature, and pulp density were used. The maximum Zn and Mn yield was the output data. It turned out that XG boost regression provided the best estimation, while linear regression was the least accurate. While the lithium-ion batteries from electric vehicles cannot be directly reused, the development of effective sorting of cells is of high importance [95]. In the study [96], the screening method for retired battery packs was shown. The support vector machine, with an accuracy of 96.8 percent, was applied. The input data come from 12 retired batteries, i.e., 240 cells, and include their capacities and resistances. It turned out that the proposed approach can reduce the time needed for sorting and four-fifths, in comparison to the manual process. In the paper [97], the sorting methods of lithium-ion batteries in large quantities were described. The degradation state of the battery was determined with X-ray radiographic scanning and digital image contrast computation. The proposed approach provides an accuracy of 79 percent. In turn, in the study [98], the Artificial Intelligence-based sorting method was applied to the recycling of unused mobile phones. As a first step, the retired batteries from mobile phones were subjected to magnetic separation, eddy current, and pyrometallurgical and hydrometallurgical processes. Next, the pictures, which were taken with purified metal, were classified with the convolutional neural network with rectified linear unit (ReLU) activation function. To increase the amount of input data, image augmentation was used.

7. Discussion

In e-waste management, it is extremely important to create an eco-system that enables their proper processing, recycling, and reuse. The recycling processes must be flexible and adaptable to the next generation of batteries [2]. That leads to sustainable battery cell production as a green technology of the future [99,100]. In turn, the information and communication technologies (ICTs) and Internet of Things-based concepts of waste collection were postulated [43,101–103]. Since smartphones and mobile applications are commonly used in the information society [104], they can also be used in waste collection. Such applications are responsible for data collection and transfer on servers. The Artificial Intelligence-based approaches are reasonable promises in data analysis. Artificial Intelligence-based algorithms can also be helpful in the estimation of the influence of the first battery life on the recycled one, and this context, the evaluation of the different recycled materials [105]. The early prediction of the battery life cycle provides a decrease in its degradation process, while it is associated with the non-linear character of this process [106]. To enable battery monitoring in real-time cloud computing, in particular cloud storage, as well as blockchain [107,108] and the digital twin-based battery cloud management system [109,110] can be applied. Moreover, high-performance processor units can accelerate the whole computational operation, including learning processes. Based on the battery field data for low dynamics and high dynamics (capacity, nominal voltage, weight, cathodes, and anode material), and impedance, the digital twin can be used for online monitoring of the electrode level [111]. In the case of the field data, several factors affect the accuracy of the identification, including the sampling rate and sensor rate. With the increase in the sampling rate, the computational and storage costs increase. The resulting sampling rate is a compromise between the accuracy of identification and the cost incurred. Thus, Artificial Intelligence-based algorithms are the promising direction in the production, manufacturing, optimization, and monitoring of batteries [20].

It is known that Artificial Intelligence-based algorithms, in particular Machine Learning techniques, require a large amount of data to be trained and tested; however, their quality is not without significance. Datasets that are too small or contain low-quality data can lead to incorrect predictions. Thus, the first step to developing Artificial Intelligence-based algorithms is the implementation of adequate acquisition, storing, and management of the data. Providing good quality, reliable data is of high importance [17]. To ensure the amount of data that is appropriate to train the models, for example, in [18] to predict the state of battery charge, a training set was created in the laboratory by applying drive cycle loads at various ambient temperatures to a Li-ion battery and supplemented with data from the public database Panasonic 18650PF Li-ion Battery Data, which includes HPPC, drive cycles, and impedance spectroscopy tests that were performed taking into account the temperature impact [112]. Taking into account the algorithms' accuracy, the most commonly used split for training to testing data that is applied in the Artificial Intelligence-based algorithms is 90% to 10%, while in many papers in the field of waste management, a 70% to 30% split for training to testing data is considered [56,113]. The relatively small amount of data might lead to overfitting issues; to avoid this, one can combine theoretical data with experimental measurements or/and apply the algorithms that are dedicated to the small dataset, for example, the hierarchical Machine Learning approach [17]. Another issue is connected with the lack of data standardization, in particular for experimental data in the material sciences [114]. Moreover, the cross-validation of different Artificial Intelligence-based algorithms should be attached to detect overfitting.

An important aspect is also data security, especially for data from households and institutions [115]. It is connected with privacy laws and a lack of regulation, to the author's knowledge, that protects personal waste, including e-waste and battery waste. This may limit the intelligent waste management systems [116] while opening access to individual household data.

On the other hand, intelligent sorting of waste materials can also significantly decrease waste management costs and increase efficiency. Thus, manual source segregation provides a higher possibility of waste recovery, a tedious and time-consuming process. The automation process will not only improve its efficiency but also positively affect the employees' health [45].

It is also worth stressing that all waste management systems, including battery waste management, consume energy, mostly from batteries in the devices/sensor used in the solutions. At the same time, they can be replaced by renewable energy sources such as photovoltaic panels for battery charge [117].

To summarize, the algorithmic performance comparison in terms of their types and accuracy has been done in Table 1. For waste classification and sorting based on image recognition algorithms like deep neural networks, region-based convolutional neural networks, convolution neural networks, support vector machines, k-nearest neighbor, and random forest were applied. Convolution neural networks provide the highest efficiency [40,118–120]. In turn, random forest, multilayer perceptron neural networks and convolution neural networks were also successfully applied to waste management [50,121], while the support vector machine and naive Bayes provide lower accuracy. For a forecast of the number of annual waste generation AI-based algorithms, including support vector machine, fuzzy logic–support vector regression, adaptive neuro-fuzzy inference system, artificial neural network, k-nearest neighbors have been proposed. It turned out that the highest accuracy of prediction can be obtained using an adaptive neuro-fuzzy inference system [55]. For the optimization of the metal recovery from battery waste using an automated neural network, linear regression, random forest regression, AdaBoost regression, gradient boosting regression, and XG boost regression were applied. It turned out that in the case of Zn recovery, the highest accuracy provides automated neural network [113], while in the case of Mn recovery, XG boost regression was used [94]. Moreover, the optimization linear regression provide the wrong prediction, namely a negative value for non-negative property, in the case of the metal recovery of Zn from battery waste.

Table 1. Comparison of the Artificial Intelligence-based, in particular Machine Learning-based algorithms in terms of application types and accuracy.

Ref.	AI-Based Algorithms	Type of Operation	Accuracy [%]	Datasets
[66]	Region-based Convolutional Neural Network	waste classification based on image recognition	81.40	800 pictures of waste (3456 × 4608, 600 pixels)
[122]	Convolution Neural Networks	waste classification based on image recognition	87.69	Garbage In Images (GINI) dataset https://github.com/spotgarbage/spotgarbage-GINI (accessed on 1 September 2022)
[67]	Region-based Convolutional Neural Network	construction waste classification based on image recognition (nails and screws)	89.10	A number of pictures of nails and screws
[42]	Convolution Neural Networks	waste classification based on image recognition	90.00	2298 pictures (i.e., 223 batteries, 91 syringes, 1984 non-hazardous trash)
[123]	Support Vector Machine k-Nearest Neighbor Random Forest	waste classification based on image recognition	93.00 93.00 93.00	1200 pictures (400 pictures for each class, i.e., glass, paper, metal, plastic)
[118]	Deep Neural Networks for Trash Classification	waste classification based on image recognition	94.00 (Trashnet dataset) 98.00 (VN-trash dataset)	5904 images of waste, divided into three classes, including Organic, Inorganic and Medical wastes (VN-trash dataset) 2400 images of waste, divided into six classes, including glass, paper, cardboard, plastic, metal, and trash (Trash-net dataset)
[124]	Support Vector Machine	waste classification based on image recognition	94.70	Pictures of waste
[125]	Convolution Neural Networks	waste classification based on image recognition	96.50	waste pictures from Google search and existing published image databases
[41]	Convolution Neural Networks Region-based Convolutional Neural Network	waste classification based on image recognition	93.30 96.70	16,384 (128 × 128) pictures of e-waste
[40]	Support Vector Machine	Solid waste classification based on image recognition	99.40	220 pictures of waste (i.e., 60 rotated bin images, 100 unrotated bin images, 800 × 600 pixels)
[119]	Convolution Neural Networks	waste classification based on image recognition	99.60	10,108 waste images (i.e., 2527 pictures of flipping horizontal, 2527 pictures of flipping vertical, and 2527 random 25° rotations)
[126]	Convolution Neural Networks	waste sorting based on image recognition	91.72	Pictures of waste (227 × 227 pixels)
[120]	Convolution Neural Networks	waste sorting based on image recognition	94.71	1040 images of waste
[63]	Convolution Neural Networks, Support Vector Machines	waste sorting based on image recognition	94.80 83.00	2000 images of waste
[127]	Convolution Neural Networks	waste sorting based on image recognition	95.00	2400 images of waste, divided into six classes, including glass, paper, cardboard, plastic, metal, and trash (Trash-net dataset)

Table 1. *Cont.*

Ref.	AI-Based Algorithms	Type of Operation	Accuracy [%]	Datasets
[68]	Support Vector Machines	COVID-19 pandemic waste sorting based on image recognition	96.50	2400 images of waste
[128]	Convolution Neural Networks	e-waste sorting based on image recognition	96.00	8000 pictures of electronic devices
[129]	Convolution Neural Networks	waste sorting based on image recognition	99.00	1241 pictures of waste
[50]	Convolution Neural Networks	waste management	96.00	200 pictures of waste
[53]	Multi-layer Perceptron Artificial Neural Network	forecast of the number of annual waste generation	95.00	solid waste generation rates (kg per capita–1 day–1) in Bahrain (1997–2016)
[121]	Support vector machine Random Forest Multilayer perceptron Naive Bayes	waste management	89.52 97.49 96.44 81.46	2947 pictures of waste
[56]	Fuzzy Logic–Support Vector Regression	estimation of waste generation rates	92.00	105 $\times$ 7 matrices, representing static data: 105 samples of 7 elements
[55]	Support Vector Machine Adaptive Neuro-fuzzy Inference System Artificial Neural Network k-Nearest Neighbours	waste generation forecasting	71.00 98.00 46.00 51.00	collection of monthly time series of waste generation from the period of eighteen years (1996–2014)
[71]	Convolutional Neural Network	waste sorting based on image recognition	70.00	2400 images of waste, divided into six classes, including glass, paper, cardboard, plastic, metal, and trash (Trash-net dataset)
[36]	Gradient-boosted decision trees (GBT) Random Forest	prediction of the characteristics of the electrodes	93.48 91.75	96 cathode-related, and 75 anode-related electrodes and half-cell data
[113]	Automated Neural Network (SANN)	optimization of metal recovery of Zn from battery waste	94.00	Experimental data-two sets of 29 data samples for Zn and Mn yield
[94]	Linear Regression Random Forest Regression AdaBoost Regression Gradient Boosting Regression XG Boost Regression	optimization of metal recovery of Zn from battery waste	−42.33 88.02 82.67 96.76 99.88	Experimental data-sets of 29 data samples for Zn yield
[94]	Linear Regression Random Forest Regression AdaBoost Regression Gradient Boosting Regression XG Boost Regression	optimization of metal recovery of Mn from battery waste	19.36 22.96 12.32 61.25 95.97	Experimental data-sets of 29 data samples for Mn yield

8. Conclusions

Despite the recent developments in battery production and battery waste management, there is still a need to fill the gap between laboratory studies and real-world applications. In this review, we presented the recent capabilities of Artificial Intelligence, in particular Machine Learning and computational intelligence to develop algorithms, which can support effective battery life cycles, from projecting and production to battery waste management and recycling in accordance with the model of the closed circular economy. It turned out that convolution neural networks provide the most effective IT tools to evaluate the classification and sorting of waste [40,118–120], in particular, battery waste based on image recognition algorithms as well as waste management [50,121], while the adaptive neuro-fuzzy inference system provides the prediction of annual waste generation with higher accuracy [55]. In effective recycling, a high percentage of recycled raw materials is an important issue. The prediction of it can also be successfully made with an Artificial Intelligence-based approach [94,113]. Some of the recommendations for future research are:

1. Since the development of efficient Artificial Intelligence-based algorithms strictly provides an adequate amount of good-quality data, the development of a standardized public database, which will contain battery data [17], for example, sleep data-national sleep research resource (NSRR, the database that contains physiological signals and clinical data [130]). In turn, many prediction algorithms can be based in part on experimental data from published papers and technical reports. Here, also involving the text mining methods to extract and analyze the results and conclusions already obtained will be good practice [131,132];

2. The analysis of the relationship between manufacturing factors and anode and cathode parameters, taking into account other battery manufacturing processes such as slurry mixing and calendaring based on an Artificial Intelligence approach [36];

3. The development of the battery multiscale models [133];

4. The development of sorting and separation technologies supported by Artificial Intelligence, which can increase the efficiency of recycling [134];

5. The development of local recycling or pretreating, which can reduce the cost of hazardous LIBs transport [135];

6. The increase in the accuracy of waste detection and identification based on Artificial Intelligence, in particular Machine Learning and computational intelligence [136];

7. Increasing the speed of data transfer, which is especially important in the part of waste management, in particular battery waste, related to efficient collection [137];

8. The security of the data, while the intelligent waste management systems open access to individual household data [115].

Moreover, strict legal regulations must also be established in the area of battery waste, including greater producer responsibility. The recycling capacity has been developed mostly in places with significant recycling regulations, like China [138]. Moreover, the European Union has suggested legislation in the area of battery collections, labeling, and recycling [139].

Author Contributions: Conceptualization and methodology, A.P., M.O. and W.U.; writing—original draft preparation, A.P., M.O. and W.U.; writing—review & editing, M.O. and W.U.; visualization, W.U.; supervision, A.P. and W.U. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

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

References

1. Battery Recycling Market Size Is Projected to Reach USD 18.96 Billion by 2030, Growing at a CAGR of 7.12%: Straits Research. Available online: https://www.globenewswire.com/en/news-release/2022/07/26/2486248/0/en/Battery-Recycling-Market-Size-is-projected-to-reach-USD-18-96-Billion-by-2030-growing-at-a-CAGR-of-7-12-Straits-Research.html (accessed on 18 September 2022).
2. Fan, E.; Li, L.; Wang, Z.; Lin, J.; Huang, Y.; Yao, Y.; Chen, R.; Wu, F. Sustainable Recycling Technology for Li-Ion Batteries and Beyond: Challenges and Future Prospects. *Chem. Rev.* **2020**, *120*, 7020–7063. [CrossRef] [PubMed]
3. Zhao, Y.; Pohl, O.; Bhatt, A.I.; Collis, G.E.; Mahon, P.J.; Rüther, T.; Hollenkamp, A.F. A Review on Battery Market Trends, Second-Life Reuse, and Recycling. *Sustain. Chem.* **2021**, *2*, 167–205. [CrossRef]
4. Waste Statistics—Recycling of Batteries and Accumulators. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_statistics_-_recycling_of_batteries_and_accumulators (accessed on 18 September 2022).

5. Zhang, Y.; Wang, B.; Cheng, Q.; Li, X.; Li, Z. Removal of toxic heavy metal ions (Pb, Cr, Cu, Ni, Zn, Co, Hg, and Cd) from waste batteries or lithium cells using nanosized metal oxides: A review. *J. Nanosci. Nanotechnol.* **2020**, *20*, 7231–7254. [CrossRef] [PubMed]
6. Palisoc, S.T.; Cansino, E.J.F.; Dy, I.M.O.; Razal, C.F.A.; Reyes, K.C.N.; Racines, L.R.; Natividad, M.T. Electrochemical determination of tannic acid using graphite electrodes sourced from waste zinc-carbon batteries. *Sens. Bio-Sens. Res.* **2020**, *28*, 100326. [CrossRef]
7. Xiao, J.; Li, J.; Xu, Z. Challenges to Future Development of Spent Lithium Ion Batteries Recovery from Environmental and Technological Perspectives. *Environ. Sci. Technol.* **2020**, *54*, 9–25. [CrossRef] [PubMed]
8. Pagliaro, M.; Meneguzzo, F. Lithium battery reusing and recycling: A circular economy insight. *Heliyon* **2019**, *5*, 01866. [CrossRef] [PubMed]
9. Baars, J.; Domenech, T.; Bleischwitz, R.; Melin, H.E.; Heidrich, O. Circular economy strategies for electric vehicle batteries reduce reliance on raw materials. *Nat. Sustain.* **2021**, *4*, 71–79. [CrossRef]
10. Habib, K.; Hansdóttir, S.T.; Habib, H. Critical metals for electromobility: Global demand scenarios for passenger vehicles, 2015–2050. *Resour. Conserv. Recycl.* **2020**, *154*, 104603. [CrossRef]
11. Liu, P. Recycling waste batteries: Recovery of valuable resources or reutilization as functional materials. *ACS Sustain. Chem. Eng.* **2018**, *6*, 11176–11185. [CrossRef]
12. Olivetti, E.A.; Ceder, G.; Gaustad, G.G.; Fu, X. Lithium-Ion Battery Supply Chain Considerations: Analysis of Potential Bottlenecks in Critical Metals Author links open overlay panel. *Joule* **2017**, *1*, 229–243. [CrossRef]
13. Liberati, A.; Altman, D.G.; Tetzlaff, J.; Mulrow, C.; Gotzsche, P.C.; Ioannidis, J.P.A.; Clarke, M.; Devereaux, P.J.; Kleijnen, J.; Moher, D. The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration. *PLoS Med.* **2009**, *6*, e1–e34. [CrossRef] [PubMed]
14. Rethlefsen, M.L.; Kirtley, S.; Waffenschmidt, S.; Ayala, A.P.; Moher, D.; Page, M.J.; Koffel, J.B. PRISMA-S: An extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews. *Syst. Rev.* **2021**, *10*, 39. [CrossRef] [PubMed]
15. Shamseer, L.; Moher, D.; Clarke, M.; Ghersi, D.; Liberati, A.; Petticrew, M.; Shekelle, P.; Stewart, L.A. Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015: Elaboration and explanation. *BMJ* **2015**, *349*, 7647. [CrossRef] [PubMed]
16. Duffner, F.; Mauler, L.; Wentker, M.; Leker, J.; Winter, M. Large-scale automotive battery cell manufacturing: Analyzing strategic and operational effects on manufacturing costs. *Int. J. Prod. Econ.* **2021**, *232*, 107982. [CrossRef]
17. Lombardo, T.; Duquesnoy, M.; El-Bouysidy, H.; Arén, F.; Gallo-Bueno, A.; Jørgensen, P.B.; Bhowmik, A.; Demortière, A.; Ayerbe, E.; Alcaide, F.; et al. Artificial Intelligence Applied to Battery Research: Hype or Reality? *Chem. Rev.* **2022**, *122*, 10899–10969. [CrossRef] [PubMed]
18. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Emadi, A.J. State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach. *J. Power Sources* **2018**, *400*, 242–255. [CrossRef]
19. Girijaprasanna, T.; Dhanamjayulu, C. A Review on Different State of Battery Charge Estimation Techniques and Management Systems for EV Applications. *Electronics* **2022**, *11*, 1795.
20. Severson, K.A.; Attia, P.M.; Jin, N.; Perkins, N.; Jiang, B.; Yang, Z.; Chen, M.H.; Aykol, M.; Herring, P.K.; Fraggedakis, D.; et al. Data-driven prediction of battery cycle life before capacity degradation. *Nat. Energy* **2019**, *4*, 383–391. [CrossRef]
21. Tan, S.W.; Huang, S.W.; Hsieh, Y.Z.; Lin, S.S. The Estimation Life Cycle of Lithium-Ion Battery Based on Deep Learning Network and Genetic Algorithm. *Energies* **2021**, *14*, 4423. [CrossRef]
22. Cunha, R.P.; Lombardo, T.; Primo, E.N.; Franco, A.A. Artificial Intelligence Investigation of NMC Cathode Manufacturing Parameters Interdependencies. *Batter. Supercaps* **2020**, *3*, 60–67. [CrossRef]
23. He, W.; Williard, N.; Chen, C.; Pecht, M. State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 783–791. [CrossRef]
24. Salkind, A.J.; Fennie, C.; Singh, P.; Atwater, T.; Reisner, D.E. Determination of state-of charge and state-of-health of batteries by fuzzy logic methodology. *J. Power Sources* **1999**, *80*, 293–300. [CrossRef]
25. Zheng, Y.; Lu, L.; Han, X.; Li, J.; Ouyang, M. $LiFePO_4$ battery pack capacity estimation for electric vehicles based on charging cell voltage curve transformation. *J. Power Sources* **2013**, *226*, 33–41. [CrossRef]
26. Xu, J.; Cao, B.; Chen, Z.; Zou, Z. An online state of charge estimation method with reduced prior battery testing information. *Int. J. Electr. Power Energy Syst.* **2014**, *63*, 178–184. [CrossRef]
27. Wu, X.; Mi, L.; Tan, W.; Qin, J.L.; Na Zhao, M. State of Charge (SOC) Estimation of Ni-MH Battery Based on Least Square Support Vector Machines. *Adv. Mater. Res.* **2011**, *211–212*, 1204–1209. [CrossRef]
28. How, D.N.; Hannan, M.; Lipu, M.H.; Sahari, K.S.; Ker, P.J.; Muttaqi, K.M. State-of-charge estimation of li-ion battery in electric vehicles: A deep neural network approach. *IEEE Trans. Ind. Appl.* **2020**, *56*, 5565–5574. [CrossRef]
29. Song, X.; Yang, F.; Wang, D.; Tsui, K.L. Combined CNN-LSTM Network for State-of-Charge Estimation of Lithium-Ion Batteries. *IEEE Access* **2019**, *7*, 88894–88902. [CrossRef]
30. Afshar, S.; Morris, K.; Khajepour, A. State-of-Charge Estimation Using an EKF-Based Adaptive Observer. *IEEE Trans. Control Syst. Technol.* **2019**, *27*, 1907–1923. [CrossRef]
31. Li, Y.; Guo, H.; Qi, F.; Guo, Z.; Li, M. Comparative Study of the Influence of Open Circuit Voltage Tests on State of Charge Online Estimation for Lithium-Ion Batteries. *IEEE Access* **2020**, *8*, 17535–17547. [CrossRef]

32. Wang, B.; Zhang, G.; Wang, H.; Xuan, J.; Jiao, K. Multi-physics-resolved digital twin of proton exchange membrane fuel cells with a data-driven surrogate model. *Energy AI* **2020**, *1*, 100004. [CrossRef]
33. Hsu, C.W.; Xiong, R.; Chen, N.Y.; Li, J.; Tsou, N.T. Deep neural network battery life and voltage prediction by using data of one cycle only. *Appl. Energy* **2022**, *306*, 118134. [CrossRef]
34. Blomeke, S.; Rickert, J.; Mennenga, M.; Thiede, S.; Spengler, T.S.; Herrmann, C. Recycling 4.0—Mapping smart manufacturing solutions to remanufacturing and recycling operations. *Procedia CIRP* **2020**, *90*, 600–605. [CrossRef]
35. Garg, A.; Mou, J.; Su, S.; Gao, L. Reconfigurable battery systems: Challenges and safety solutions using intelligent system framework based on digital twins. *IET Collab. Intell. Manuf.* **2022**, *4*, 232–248. [CrossRef]
36. Niri, M.F.; Liu, K.; Apachitei, G.; Roman-Ramirez, L.A.A.; Lain, M.; Widanage, D.; Marco, J. Quantifying key factors for optimised manufacturing of Li-ion battery anode and cathode via artificial intelligence. *Energy AI* **2022**, *7*, 100129. [CrossRef]
37. Cerchecci, M.; Luti, F.; Mecocci, A.; Parrino, S.; Peruzzi, G.; Pozzebon, A. A low power IoT sensor node architecture for waste management within smart cities context. *Sensors* **2018**, *18*, 1282. [CrossRef] [PubMed]
38. Khoa, T.A.; Phuc, C.H.; Lam, P.D.; Nhu, L.M.B.; Trong, N.M.; Phuong, N.T.H.; Dung, N.V.; Tan-Y, N.; Nguyen, H.N.; Duc, D.N.M. Waste Management System Using IoT-Based Machine Learning in University. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 6138637.
39. Gutierrez, J.M.; Jensen, M.; Henius, M.; Riaz, T. Smart waste collection system based on location intelligence. *Procedia Comput. Sci.* **2015**, *61*, 120–127. [CrossRef]
40. Aziz, F.; Arof, H.; Mokhtar, N.; Mubin, M.; Abu Talip, M.S. Rotation invariant bin detection and solid waste level classification. *Measurement* **2015**, *65*, 19–28. [CrossRef]
41. Nowakowski, P.; Pamuła, T. Application of deep learning object classifier to improve e-waste collection planning Author links open overlay panel. *Waste Manag.* **2020**, *109*, 1–9. [CrossRef] [PubMed]
42. Hua, D.; Gao, J.; Mayo, R.; Smedley, A.; Puranik, P.; Zhan, J. Segregating Hazardous Waste Using Deep Neural Networks in Real-Time Video. In Proceedings of the 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 6–8 January 2020; pp. 1016–1022.
43. Chen, J.; Huang, S.; BalaMurugan, S.; Tamizharasi, G.S. Artificial intelligence based e-waste management for environmental planning. *Environ. Impact Assess. Rev.* **2021**, *87*, 106498. [CrossRef]
44. Han, W.; Gao, G.; Geng, J.; Li, Y.; Wang, Y. Ecological and health risks assessment and spatial distribution of residual heavy metals in the soil of an e-waste circular economy park in Tianjin, China. *Chemosphere* **2018**, *197*, 325–335. [CrossRef]
45. Ihsanullah, I.; Alam, G.; Jamal, A.; Shaik, F. Recent advances in applications of artificial intelligence in solid waste management: A review. *Chemosphere* **2022**, *309*, 136631. [CrossRef]
46. Sinthiya, N.J.; Chowdhury, T.A.; Haque, A.K.M.B. Artificial Intelligence Based Smart Waste Management—A Systematic Review. In *Computational Intelligence Techniques for Green Smart Cities. Green Energy and Technology*; Lahby, M., Al-Fuqaha, A., Maleh, Y., Eds.; Springer: Cham, Switzerland, 2022.
47. Menegaki, M.; Damigos, D. A review on current situation and challenges of construction and demolition waste management. *Curr. Opin. Green Sustain. Chem.* **2018**, *13*, 8–15. [CrossRef]
48. Islam, R.; Nazifa, T.H.; Yuniarto, A.; Uddin, A.S.; Salmiati, S.; Shahid, S. An empirical study of construction and demolition waste generation and implication of recycling. *Waste Manag.* **2019**, *95*, 10–21. [CrossRef]
49. Qu, D. Application of Artificial Intelligence in Waste Classification Management at University. In *Proceedings in Adaptation, Learning and Optimization, Proceedings of the International Conference on Intelligent Vision and Computing (ICIVC 2021), Qingdao, China, 23–25 July 2021*; Sharma, H., Vyas, V.K., Pandey, R.K., Prasad, M., Eds.; Springer: Cham, Switzerland, 2021; Volume 5.
50. Jude, A.B.; Singh, D.; Islam, S.; Jameel, M.; Srivastava, S.; Prabha, B.; Kshirsagar, P.R. An Artificial Intelligence Based Predictive Approach for Smart Waste Management. *Wirel. Pers. Commun.* **2021**. [CrossRef]
51. Huang, J.; Koroteevabc, D.D. Artificial intelligence for planning of energy and waste management. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101426. [CrossRef]
52. Ali, T.H.; Akhund, M.A.; Memon, N.A.; Memon, A.H.; Imad, H.U.; Khahro, S.H. Application of Artifical Intelligence in Construction Waste Management. In Proceedings of the 8th International Conference on Industrial Technology and Management (ICITM) 2019, Cambridge, UK, 2–4 March 2019; pp. 50–55.
53. Coskuner, G.; Jassim, M.S.; Zontul, M.; Karateke, S. Application of artificial intelligence neural network modeling to predict the generation of domestic, commercial and construction wastes. *Waste Manag. Res.* **2021**, *39*, 499–507. [CrossRef]
54. Soni, U.; Roy, A.; Verma, A.; Jain, V. Forecasting municipal solid waste generation using artificial intelligence models—A case study in India. *SN Appl. Sci.* **2019**, *1*, 162. [CrossRef]
55. Abbasi, M.; El Hanandeh, A. Forecasting municipal solid waste generation using artificial intelligence modelling approaches. *Waste Manage.* **2016**, *56*, 13–22. [CrossRef]
56. Golbaz, S.; Nabizadeh, R.; Sajadi, H.S. Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence. *J. Environ. Health Sci. Eng.* **2019**, *17*, 41–51. [CrossRef]
57. Abdallaha, M.; Talib, M.A.; Feroz, S.; Nasir, Q.; Abdalla, H.; Mahfood, B. Artificial intelligence applications in solid waste management: A systematic research review. *Waste Manag.* **2020**, *109*, 231–246. [CrossRef] [PubMed]
58. McKinnon, D.; Fazakerley, J.; Hultermans, R. *Waste Sorting Plants—Extracting Value from Waste*; ISWA: Vienna, Austria, 2017.
59. Abdoli, S. RFID Application in municipally solid waste management system. *Int. J. Environ. Res.* **2009**, *3*, 447–454.

60. Sakr, G.E.; Mokbel, M.; Darwich, A.; Khneisser, M.N.; Hadi, A. Comparing deep learning and support vector machines for autonomous waste sorting. In Proceedings of the IEEE International Multidisciplinary Conference on Engineering Technology (IMCET) 2016, Beirut, Lebanon, 2–4 November 2016; pp. 207–212.
61. Gundupalli, S.P.; Hait, S.; Thakur, A. A review on automated sorting of source-separated municipal solid waste for recycling. *Waste Manag.* **2017**, *60*, 56–74. [CrossRef] [PubMed]
62. Zenrobotics. Available online: https://zenrobotics.com (accessed on 19 October 2022).
63. Artificial Intelligence amd Robotization in Waste Sorting Centers as an Alternative to Brown Bins. Available online: https://www.biogasworld.com/news/artificial-intelligence-robotization-waste-sorting-centers-alternative-brown-bins/ (accessed on 19 October 2022).
64. Wilts, H.; Garcia, B.R.; Garlito, R.G.; Gómez, L.S.; Prieto, E.G. Artificial Intelligence in the Sorting of Municipal Waste as an Enabler of the Circular Economy. *Resources* **2021**, *10*, 28. [CrossRef]
65. Kshirsagar, P.R.; Kumar, N.; Almulihi, A.H.; Alassery, F.; Khan, A.I.; Islam, S.; Rothe, J.P.; Jagannadham, D.B.V.; Dekeba, K. Artificial Intelligence-Based Robotic Technique for Reusable Waste Materials. *Comput. Intell. Neurosci.* **2022**, *2022*, 2073482. [CrossRef] [PubMed]
66. Sousa, J.; Rebelo, A.; Cardoso, J.S. Automation of Waste Sorting with Deep Learning. In Proceedings of the XV Workshop de Visão Computacional (WVC) 2019, São Bernardo do Campo, Brazil, 9–11 September 2019; pp. 43–48.
67. Wang, Z.; Li, H.; Zhang, X. Construction waste recycling robot for nails and screws: Computer vision technology and neural network approach. *Autom. Constr.* **2019**, *97*, 220–228. [CrossRef]
68. Kumar, N.M.; Mohammed, M.A.; Abdulkareem, K.H.; Damasevicius, R.; Mostafa, S.A.; Maashi, M.S.; Chopra, S.S. Artificial intelligence-based solution for sorting COVID related medical waste streams and supporting data-driven decisions for smart circular economy practice. *Process Saf. Environ. Prot.* **2021**, *152*, 482–494. [CrossRef]
69. Subramanian, A.; Thayalan, D.; Edwards, A.; Al-Malki, A.E.; Venugopal, A. Biomedical waste management in dental practice and its significant environmental impact: A perspective. *Environ. Technol. Innov.* **2021**, *24*, 101807. [CrossRef]
70. Shaida, M.N.; Singla, S. Global biomedical waste management issues and practices. *Int. J. Innov. Technol. Expl. Eng.* **2019**, *8*, 1053–1059.
71. Abeygunawardhana, A.G.D.T.; Shalinda, R.M.M.M.; Bandara, W.H.M.D.; Anesta, W.D.S.; Kasthurirathna, D.; Abeysiri, L. AI—Driven Smart Bin for Waste Management. In Proceedings of the 2nd International Conference on Advancements in Computing (ICAC) 2020, Malabe, Sri Lanka, 10–11 December 2020; pp. 482–487.
72. Zhang, C.; Hu, M.; Di Maio, F.; Sprecher, B.; Yang, X.; Tukker, A. An overview of the waste hierarchy framework for analyzing the circularity in construction and demolition waste management in Europe. *Sci. Total Environ.* **2022**, *803*, 149892. [CrossRef] [PubMed]
73. Deshwal, D.; Sangwan, P.; Dahiya, N. Economic Analysis of Lithium Ion Battery Recycling in India. *Wirel. Pers. Commun.* **2022**, *124*, 3263–3286. [CrossRef]
74. Harper, G.; Sommerville, R.; Kendrick, E.; Driscoll, L.; Slater, P.; Stolkin, R.; Walton, A.; Christensen, P.; Heidrich, O.; Lambert, S.; et al. Recycling lithium-ion batteries from electric vehicles. *Nature* **2019**, *575*, 75–86. [CrossRef]
75. Doose, S.; Mayer, J.K.; Michalowski, P.; Kwade, A. Challenges in Ecofriendly Battery Recycling and Closed Material Cycles: A Perspective on Future Lithium Battery Generations. *Metals* **2021**, *11*, 291. [CrossRef]
76. Golmohammadzadeh, R.; Faraji, F.; Jong, B.; Pozo-Gonzalo, C.; Chakraborty, P.; Banerjee. Current challenges and future opportunities toward recycling of spent lithium-ion batteries. *Renew. Sust. Energ. Rev.* **2022**, *159*, 112202. [CrossRef]
77. Heelan, J.; Gratz, E.; Zheng, Z.; Wang, Q.; Chen, M.; Apelian, D.; Wang, Y. Current and Prospective Li-Ion Battery Recycling and Recovery Processes. *JOM* **2016**, *68*, 2632–2638. [CrossRef]
78. Brückner, L.; Frank, J.; Elwert, T. Industrial Recycling of Lithium-Ion Batteries—A Critical Review of Metallurgical Process Routes. *Metals* **2020**, *10*, 1107. [CrossRef]
79. Hiskey, B. Metallurgy, Survey. In *Encyclopedia of Chemical Technology*; Kirk, R.E., Othmer, D.F., Eds.; Wiley: New York, NY, USA, 2003.
80. Zhang, G.; He, Y.; Wang, H.; Feng, Y.; Xie, W.; Zhu, X. Application of mechanical crushing combined with pyrolysis-enhanced flotation technology to recover graphite and $LiCoO_2$ from spent lithium-ion batteries. *J. Clean. Prod.* **2019**, *231*, 1418–1427. [CrossRef]
81. Makuza, B.; Tian, Q.; Guo, X.; Chattopadhyay, K.; Yu, D. Pyrometallurgical options for recycling spent lithium-ion batteries: A comprehensive review. *J. Power Sources* **2021**, *491*, 229622. [CrossRef]
82. Rajaeifar, M.A.; Raugei, M.; Steubing, B.; Hartwell, A.; Anderson, P.A.; Heidrich, O. Life cycle assessment of lithium-ion battery recycling using pyrometallurgical technologies. *J. Ind. Ecol.* **2021**, *25*, 1560–1571. [CrossRef]
83. Yao, Y.; Zhu, M.; Zhao, Z.; Tong, B.; Fan, Y.; Hua, Z. Hydrometallurgical Processes for Recycling Spent Lithium-Ion Batteries: A Critical Review. *ACS Sustainable Chem. Eng.* **2018**, *6*, 13611–13627. [CrossRef]
84. Shin, S.M.; Kim, N.H.; Sohn, J.S.; Yang, D.H.; Kim, Y.H. Development of a metal recovery process from Li-ion battery wastes. *Hydrometallurgy* **2005**, *79*, 172–181. [CrossRef]
85. Peng, C.; Hamuyuni, J.; Wilson, B.P.; Lundström, M. Selective reductive leaching of cobalt and lithium from industrially crushed waste Li-ion batteries in sulfuric acid system. *Waste Manag.* **2018**, *76*, 582–590. [CrossRef]

86. Fan, X.; Song, C.; Lu, X.; Shi, Y.; Yang, S.; Zheng, F.; Huang, Y.; Liu, K.; Wang, H.; Li, Q. Separation and recovery of valuable metals from spent lithium-ion batteries via concentrated sulfuric acid leaching and regeneration of LiNi1/3Co1/3Mn1/3O2. *J. Alloys Compd.* **2021**, *863*, 158775. [CrossRef]
87. Choi, J.W.; Cho, C.W.; Yun, Y.S. Organic acid-based linear free energy relationship models for green leaching of strategic metals from spent lithium-ion batteries and improvement of leaching performance. *J. Hazard. Mater.* **2022**, *423*, 127214. [CrossRef]
88. Sidiq, A.L.; Floweri, O.; Karunawan, J.; Abdillah, O.B.; Santosa, S.P.; Iskandar, F. NCM cathode active materials reproduced from end-of-life Li-ion batteries using a simple and green hydrometallurgical recycling process. *Mater. Res. Bull.* **2022**, *153*, 111901. [CrossRef]
89. Roy, J.J.; Srinivasan, M.; Cao, B. Bioleaching as an Eco-Friendly Approach for Metal Recovery from Spent NMC-Based Lithium-Ion Batteries at a High Pulp Density. *ACS Sustain. Chem. Eng.* **2021**, *9*, 3060–3069.
90. Horeh, N.B.; Mousavi, S.M.; Shojaosadati, S.A. Bioleaching of valuable metals from spent lithium-ion mobile phone batteries using Aspergillus niger. *J. Power Sources* **2016**, *320*, 257–266. [CrossRef]
91. Xin, Y.; Guo, X.; Chen, S.; Wang, J.; Wu, F.; Xin, B. Bioleaching of valuable metals Li, Co, Ni and Mn from spent electric vehicle Li-ion batteries for the purpose of recovery. *J. Clean. Prod.* **2016**, *116*, 249–258. [CrossRef]
92. Roy, J.J.; Cao, B.; Madhavi, S. A review on the recycling of spent lithium-ion batteries (LIBs) by the bioleaching approach. *Chemosphere* **2021**, *282*, 130944. [CrossRef]
93. Ozdemir, M.E.; Ali, Z.; Subeshan, B.; Asmatulu, E. Applying machine learning approach in recycling. *J. Mater. Cycles Waste Manag.* **2021**, *23*, 855–871. [CrossRef]
94. Priyadarshini, J.; Elangovan, M.; Mahdal, M.; Jayasudha, M. Machine-Learning-Assisted Prediction of Maximum Metal Recovery from Spent Zinc–Manganese Batteries. *Processes* **2022**, *10*, 1034. [CrossRef]
95. Garg, A.; Yun, L.; Gao, L.; Putungan, D.B. Development of Recycling Strategy for Large Stacked Systems: Experimental and Machine Learning Approach to Form Reuse Battery Packs for Secondary Applications. *J. Clean. Prod.* **2020**, *275*, 124152. [CrossRef]
96. Zhou, Z.; Duan, B.; Kang, Y.; Shang, Y.; Cui, N.; Chang, L.; Zhang, C. An efficient screening method for retired lithium-ion batteries based on support vector machine. *J. Clean. Prod.* **2020**, *67*, 121882. [CrossRef]
97. Chen, H.; Shen, J. A degradation-based sorting method for lithium-ion battery reuse. *PLoS ONE* **2017**, *12*, e0185922. [CrossRef]
98. Senthilselvi, A.; Sellam, V.; Alahmari, S.A.; Rajeyyagari, S. Accuracy enhancement in mobile phone recycling process using machine learning technique and MEPH process. *Environ. Technol. Innov.* **2020**, *20*, 101137. [CrossRef]
99. Gawel, E.; Strunz, S.; Lehmann, P.; Purkus, A. (Eds.) *The European Dimension of Germany's Energy Transition. Opportunities and Conflicts*; Springer International Publishing: Cham, Switzerland, 2019.
100. Titirici, M.M. Sustainable Batteries—Quo Vadis? *Adv. Energy Mater.* **2021**, *11*, 2003700. [CrossRef]
101. Esmaeilian, B.; Wang, B.; Lewis, K.; Duarte, F.; Ratti, C.; Behdad, S. The future of waste management in smart and sustainable cities: A review and concept paper. *Waste Manag.* **2018**, *81*, 177–195. [CrossRef]
102. Xue, Y.; Wen, Z.; Bressers, H.; Ai, N. Can intelligent collection integrate informal sector for urban resource recycling in China? *J. Clean. Prod.* **2019**, *208*, 307–315. [CrossRef]
103. Pardini, K.; Rodrigues, J.J.P.C.; Kozlov, S.A.; Kumar, N.; Furtado, V. IoT-Based Solid Waste Management Solutions: A Survey. *J. Sens. Actuator Netw.* **2019**, *8*, 5. [CrossRef]
104. Sohn, S. A contextual perspective on consumers' perceived usefulness: The case of mobile online shopping. *J. Retail. Consum. Serv.* **2017**, *38*, 22–33. [CrossRef]
105. Wu, B.; Widanage, W.D.; Yang, S.; Liu, X. Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy AI* **2020**, *1*, 100016. [CrossRef]
106. Saha, B.; Goebel, K. Battery data set. In *NASA Ames Prognostics. Data Repository*; NASA Ames Research Center: Moffett Field, CA, USA, 2007.
107. Christidis, K.; Devetsikiotis, M. Blockchains and smart contracts for the internet of things. *IEEE Access* **2016**, *4*, 2292–2303. [CrossRef]
108. Junior, C.A.R.; Sanseverino, E.R.; Gallo, P.; Koch, D.; Schweiger, H.G.; Zanin, H. Blockchain review for battery supply chain monitoring and battery trading. *Renew. Sustain. Energy Rev.* **2022**, *157*, 112078. [CrossRef]
109. Ghosh, N.; Garg, A.; Li, W.; Gao, L.; Nguyen-Thoi, T. Engineering design of battery module for EVs: Comprehensive framework development based on DFT, topology optimization, machine learning, multidisciplinary design optimization and digital twins. *J. Electrochem. Energy Convers. Storage* **2021**, *19*, 1–34. [CrossRef]
110. Garg, A.; Wei, L.; Goyal, A.; Cui, X.; Gao, L. Evaluation of batteries residual energy for battery pack recycling: Proposition of stack stress-coupled-AI approach. *J. Energy Storage* **2019**, *26*, 101001. [CrossRef]
111. Li, W.; Chen, J.; Quade, K.; Luder, D.; Gong, J.; Sauer, D.U. Battery degradation diagnosis with field data, impedance-based modeling and artificial intelligence. *Energy Storage Mater.* **2022**, *53*, 391–403. [CrossRef]
112. Panasonic 18650PF Li-ion Battery Data. Available online: https://data.mendeley.com/datasets/wykht8y7tg/1 (accessed on 19 October 2022).
113. Ruhatiya, C.; Shaosen, S.; Wang, C.-T.; Jishnu, A.K.; Bhalerao, Y. Optimization of process conditions for maximum metal recovery from spent zinc-manganese batteries: Illustration of statistical based automated neural network approach. *Energy Storage* **2020**, *2*, 111. [CrossRef]

114. Jackson, M.; Simmons, J.P.; de Graef, M. MXA: A customizable HDF5-based data format for multi-dimensional data sets. *Modell. Simul. Mater. Sci. Eng.* **2010**, *18*, 065008. [CrossRef]
115. Franca, A.S.L.; Neto, J.A.; Goncalves, R.F.; Almeida, C.M.V.B. Proposing the use of blockchain to improve the solid waste management in small municipalities. *J. Clean. Prod.* **2020**, *244*, 118529. [CrossRef]
116. Schafer, B. D-waste: Data disposal as challenge for waste management in the inter-net of things. *Int. Rev. Inform. Ethics* **2014**, *22*, 12.
117. Banu, M.I.N.; Florence, S.M. Convergence of Artificial Intelligence in IoT Network for the Smart City—Waste Management System. In *Expert Clouds and Applications. Lecture Notes in Networks and Systems*; Jacob, I.J., Gonzalez-Longatt, F.M., Shanmugam, S.K., Izonin, I., Eds.; Springer: Singapore, 2019; Volume 209.
118. Vo, A.H.; Son, L.H.; Vo, M.T.; Le, T. A Novel Framework for Trash Classification Using Deep Transfer Learning. *IEEE Access* **2019**, *7*, 178631–178639. [CrossRef]
119. Mao, W.-L.; Chen, W.-C.; Wang, C.-T.; Lin, Y.-H. Recycling waste classification using optimized convolutional neural network. *Resour. Conserv. Recycl.* **2021**, *164*, 105132. [CrossRef]
120. Zhang, S.; Chen, Y.; Yang, Z.; Gong, H. Computer Vision Based Two-stage Waste Recognition-Retrieval Algorithm for Waste Classification. *Resour. Conserv. Recycl.* **2021**, *169*, 105543. [CrossRef]
121. Khan, R.; Kumar, S.; Srivastava, A.K.; Dhingra, N.; Gupta, M.; Bhati, N.; Kumari, P. Machine Learning and IoT-Based Waste Management Model. *Comput. Intell. Neurosci.* **2021**, *2021*, 5942574. [CrossRef]
122. Mittal, G.; Yagnik, K.B.; Garg, M.; Krishnan, N.C. SpotGarbage: Smartphone app to detect garbage using deep learning. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16), Heidelberg, Germany, 12–16 September 2016; Association for Computing Machinery: New York, NY, USA, 2016; pp. 940–945.
123. Costa, B.S.; Bernardes, A.C.S.; Pereira, J.V.A.; Zampa, V.H.; Pereira, V.A.; Matos, G.F.; Soares, E.A.; Soares, C.L.; Silva, A.F. Artificial Intelligence in Automated Sorting in Trash Recycling. In *Anais do XV Encontro Nacional de Inteligência Artificial e Computacional*; SBC: Porto Alegre, Brazil, 2018; pp. 198–205.
124. Wang, Z.; Peng, B.; Hwuang, Y.; Sun, G. Classification for plastic bottles recycling based on image recognition. *Waste Manag.* **2019**, *88*, 170–181. [CrossRef]
125. Huang, G.-L.; He, J.; Xu, Z.; Huang, G. A combination model based on transfer learning for waste classification. *Concurrency Computat. Pract. Exper.* **2020**, *32*, 5751. [CrossRef]
126. Bobulski, J.; Kubanek, M. Waste Classification System Using Image Processing and Convolutional Neural Networks. In *Advances in Computational Intelligence. IWANN 2019*; Lecture Notes in Computer Science; Rojas, I., Joya, G., Catala, A., Eds.; Springer: Cham, Switzerland, 2019; Volume 11507.
127. Bircanoğlu, C.; Atay, M.; Beser, F.; Genc, O.; Kizrak, M.A. RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks. In Proceedings of the Innovations in Intelligent Systems and Applications (INISTA) 2018, Thessaloniki, Greece, 3–5 July 2018; pp. 1–7.
128. Madhav, A.S.; Rajaraman, R.; Harini, S.; Kiliroor, C.C. Application of artificial intelligence to enhance collection of E-waste: A potential solution for household WEEE collection and segregation in India. *Waste Manag. Res.* **2022**, *40*, 1047–1053. [CrossRef]
129. Gondal, A.U.; Sadiq, M.I.; Ali, T.; Irfan, M.; Shaf, A.; Aamir, M.; Shoaib, M.; Glowacz, A.; Tadeusiewicz, R.; Kantoch, E. Real Time Multipurpose Smart Waste Classification Model for Efficient Recycling in Smart Cities Using Multilayer Convolutional Neural Network and Perceptron. *Sensors* **2021**, *21*, 4916. [CrossRef]
130. National Sleep Research Resource. Available online: https://sleepdata.org/ (accessed on 19 October 2022).
131. Torayev, A.; Magusin, P.C.M.M.; Grey, C.P.; Merlet, C.; Franco, A.A. Text Mining Assisted Review of the Literature on Li-O_2 Batteries. *J. Phys. Mater.* **2019**, *2*, 044004. [CrossRef]
132. El-Bousiydy, H.; Lombardo, T.; Primo, E.N.; Duquesnoy, M.; Morcrette, M.; Johansson, P.; Simon, P.; Grimaud, A.; Franco, A.A. What can text mining tell us about Lithium-Ion battery researchers' habits? *Batter. Supercaps* **2021**, *4*, 689. [CrossRef]
133. Gayon-Lombardo, A.; Mosser, L.; Brandon, N.P.; Cooper, S.J. Pores for Thought: The Use of Generative Adversarial Networks for the Stochastic Reconstruction of 3D Multi-Phase Electrode Microstructures with Periodic Boundaries. *Comput. Mater.* **2020**, *6*, 82. [CrossRef]
134. Baduge, S.K.; Thilakarathna, S.; Perera, J.S.; Arashpour, M.; Sharafi, P.; Teodosio, B.; Shringi, A.; Mendis, P. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Autom. Contr.* **2022**, *141*, 104440. [CrossRef]
135. Yu, X.; Li, W.; Gupta, V.; Gao, H.; Tran, D.; Sarwar, S.; Chen, Z. Current Challenges in Efficient Lithium-Ion Batteries' Recycling: A Perspective. *Glob. Chall.* **2022**, *2022*, 2200099. [CrossRef]
136. Yu, K.H.; Zhang, Y.; Li, D.; Montenegro-Marin, C.E.; Kumar, P.M. Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence. *Environ. Impact Assess. Rev.* **2021**, *86*, 106492. [CrossRef]
137. Rahman, M.W.; Islam, R.; Hasan, A.; Bithi, N.I.; Hasan, M.; Rahman, M.M. Intelligent waste management system using deep learning with IoT. *J. King Saud Univ. Comput. Inf. Sci.* **2022**, *34*, 2072–2087. [CrossRef]
138. Bird, R.; Baum, Z.J.; Yu, X.; Ma, J. The Regulatory Environment for Lithium-Ion Battery Recycling. *ACS Energy Lett.* **2022**, *7*, 736–740. [CrossRef]
139. Ali, H.; Khan, H.A.; Pecht, M. Preprocessing of spent lithium-ion batteries for recycling: Need, methods, and trends. *Renew. Sustain. Energy Rev.* **2022**, *168*, 112809. [CrossRef]