AI-Driven Value Assessment for Intelligent Remanufacturing

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Abstract. This paper aims to introduce an Artificial Intelligence (AI) guided computational framework for the automatic identification, inspection, assessment, and remanufacturing of end-of-use products. The proposed framework consists of three main steps: (1) developing computer vision and image processing algorithms for analyzing product teardown images, (2) quantifying the economic and environmental value of remanufacturing from product images, and (3) developing recommender algorithms to identify the best recovery decision for each device. The paper discusses the importance of advancing object detection, image segmentation, and machine learning algorithms to automatically compute the value embedded in discarded items and developing recommendation systems to determine remanufacturing operations from product configurations. The main focus of the paper is on the value assessment and remanufacturing of electronic waste (e-waste). The paper emphasizes the need for developing object detection for identifying small objects (e.g., screws, bolts, snaps) and overlapped components (e.g., cables, printed circuit boards) standard in the design of consumer electronics by incorporating product shapes and features. The proposed value assessment framework has applications beyond remanufacturing and can be used in take-back programs and other business models that benefit from product serialization and assessment of individual devices.

Keywords: Smart Remanufacturing, Value Assessment, AI, Electronic Waste

1 Introduction: Remanufacturing of Consumer Electronics

Despite the importance of remanufacturing due to environmental considerations, resource scarcity, legislative pressure, and national security, remanufacturing has not reached its full potential and it is still a big challenge to remanufacture products at a competitive cost in the US. The profitability of remanufacturing is hampered by many factors, including the variability of used products, the labor-intensive nature of recovery operations, the scarcity of skilled workforce, and the lack of infrastructure and proper technology to empower the remanufacturing workforce [1]–[3].

One specific area of remanufacturing that requires extensive R&D and a workforce with specialized knowledge is the remanufacturing of electronic components [4].

Electronic waste is the fastest-growing waste stream in the US and many other developed regions [5] where it reached an all-time high of 53.6 million metric tons worldwide in 2019, equivalent to an average of 7.3 kg per capita, out of which only 17.4% was officially documented as recycled [6]. While the global recycling rate is 17.4%, the rate of e-waste formally recycled in America is substantially lower, 9.4% [6].

Several factors limit the proper remanufacturing of electronics: Consumer electronics are very complex in design, where up to 69 elements from the periodic table can be found in them [7]; moreover, they have a very short turnaround time where various designs, brands, and models are released to the market each year [8]. The vast product variety and the need for handling each device individually by human workers make remanufacturing very costly.

Currently, remanufacturing starts with the return and collection of cores. Collected cores are manually inspected based on their type and condition where the necessary information is extracted by an operator and entered manually via a user interface. Manual inspection is particularly challenging since often product variants differ only by small characteristics, and further identification features can no longer be recognizable due to degradation, dirt, deformation, and missing parts [9].

The objective of this paper is to introduce a framework that acts as a digital assistant to remanufacturing workforce aiming to reduce manual input errors and make identification more reliable. The proposed framework standardizes the process by making the process more objective, supports human workers by providing a second opinion in selection (e.g. known as four-eye principles), and develops more advanced checklists as AI systems can test and interpret more complex features during the assessment process.

The proposed framework assesses the value of used devices, clusters them, and suggests the required set of recovery decisions, operations, and tools according to their unique design. Figure 1 shows how AI algorithms can be used to extract remanufactureability, disassembleability, and other Re-X scores for used products.

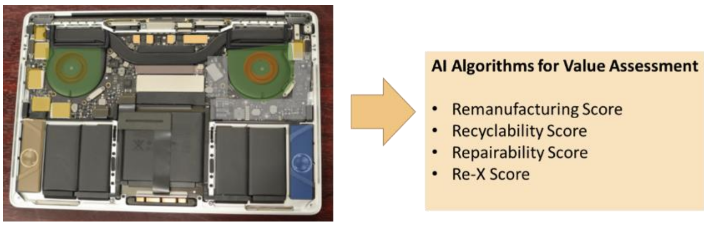

Fig. 1. Semantic segmentation of consumer electronics filled with overlapped and tiny parts

2 Background: AI in Remanufacturing

Tapping the capabilities of deep learning for sorting and classification of the waste stream has received significant attention in recent literature. Image processing techniques have largely been used for sorting plastic bottles [10], batteries [11], solid waste [12], [13], detecting the waste level in trash cans [14], and the type of waste in waste flows [15], [16]. Besides the general waste stream, deep learning has been adapted to the e-waste field as well [17]. To name a few studies, Nowakowski and Pamuła [18] developed a faster region-based convolutional neural network (R-CNN) to detect the category and size of the electronic device. Jahanian et al. [19] compared the performance of different convolutional neural networks (CNNs) in finding the boundaries of small parts inside dense circuit boards. Bassiouny et al. [20] employed different CNNs to detect precious materials in a laptop. Abou Baker et al. [21] used transfer learning for the automatic detection of cellphone models. Rojas et al. showed that instance segmentation algorithms can precisely detect complex shapes of electronics' inner parts [22]. Hu et al. utilized several CNN architectures to recognize the brand of laptops [23].

However, the available literature is primarily focused on simple object detection of large items with the broad intention of waste sorting based on general features such as product type, model, and brand. However, this paper emphasizes the importance of detecting small and overlapping objects as they are scientifically complicated.

3 The Proposed Framework for Intelligent Remanufacturing

The proposed AI framework aims to advance the remanufacturing of consumer electronics by considering the complex and uncertain nature of the waste stream. The proposed framework includes three main steps: (1) develop high-performance image processing algorithms, (2) develop value estimation methods, and (3) develop a set of recommender algorithms to determine the best recovery option and tools and equipment for each product cluster. Figure 2. shows an overview of the proposed AI framework.

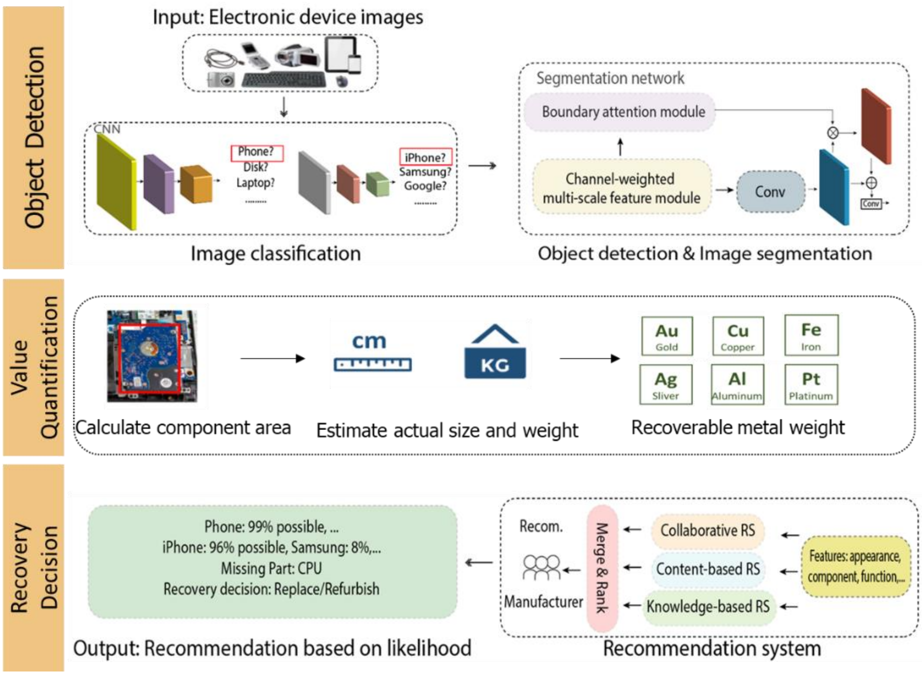

Fig. 2. The proposed framework for integration of image processing and recommender systems to handle the variability of e-waste streams.

3.1 Step 1: Development of Trainable Object Detection and Image Segmentation Algorithms

The first step of the proposed framework focuses on the design and development of image-processing networks. To make such networks practical for consumer electronics, object detection, and semantic segmentation algorithms should be competent in detecting tiny objects and learning shape features. The computer vision community has seen significant progress in object detection due to the growth of deep convolutional neural networks; however, detecting tiny objects remains an open challenge.

Detecting small objects such as fasteners, screws, cables, and joint parts is essential as it often dictates the tools and procedures needed for handling each product. Due to the variable size, shape, and location of small cables, screws, and overlapping parts, image segmentation of consumer electronics teardowns is challenging. Despite the availability of segmentation architectures for small objects [24], [25], particularly in the Unmanned Aerial Vehicle (UAV) domain [26], it is still hard to compare the performance of existing algorithms for product teardowns since the current algorithms are not evaluated for small overlapping objects suitable for the current complicated design of consumer electronics.

To address this gap, semantic segmentation methods should be advanced. Semantic segmentation tries to associate each pixel of an image with a class label. The aim is to predict the label, location, and accurate shape information for each object. Image segmentation has a rich history, where various techniques such as edge detection, thresholding, region-dependent, fuzzy, and recently neural network methods [27] such as SegNet [28], U-Net [29], and Mask R-CNN [30] developed by Facebook AI Research. The previous semantic segmentation models can be categorized into three groups: generative graphical model [31], [32], deep convolutional neural network (DCNN) based models [33], [34], and fully convolutional networks (FCN) based models [35], [36].

The recent state-of-the-art semantic segmentation methods are mainly based on FCN [35], [37]. Most recently, Transformers that have been successfully used for natural language processing tasks have shown promising results for computer vision tasks [38]. Transformers are called sequence-to-sequence architectures and treat an image as a sequence of patches. They consist of an Encoder and a Decoder. The encoder decreases the feature maps and gets rich semantic representations, while the decoder gradually retrieves the spatial information or merges multi-scale features for predicting the semantic category of each pixel from a given label set. Recent studies have shown that combining Transformers with CNN-based semantic segmentation models is very promising [39], [40].

Figure 3 shows an example of an encoder-decoder architecture based on transformers. The self-attention mechanisms of transformers, which explicitly model all pairwise interactions between elements in a sequence, make it particularly suitable for specific constraints on overlapping prediction such as removing duplicate predictions.

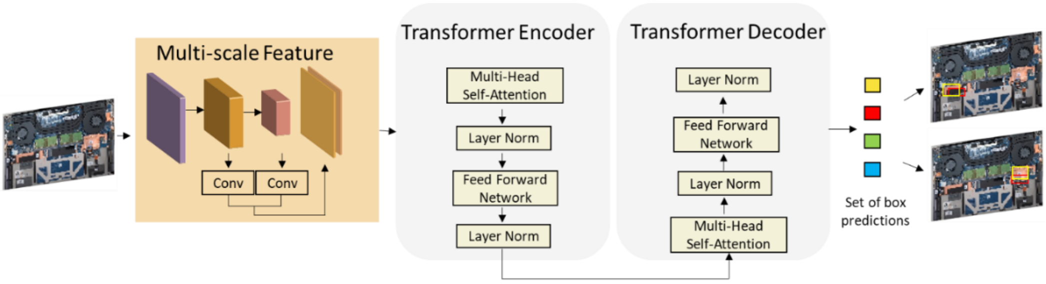

Fig. 3. Example of an object detection architecture for detecting overlapping objects

3.2 Step 2: Develop Value Calculation Methods

Once the target information (e.g., device type, condition, model, screw type, the boundary of objects, parts with hazardous materials, an estimated area of a printed circuit board) are extracted from object detection and segmentation networks, they will be linked to proper databases to calculate the economic and environmental values. Estimation techniques, the Lifecycle Assessment Analysis (LCA) conducted in SimaPro, and publicly available datasets that include detailed specifications of electronic parts (e.g., Digi-Key, Octopart, Texas instruments reports) are examples of methods that can be used to calculate the value. The value calculation approaches vary based on the objective of the analysis (e.g., the recovery weight of materials, embodied energy, and risk of toxic materials). For example, once the hard disk drive region is detected, the area and weight can be calculated, and finally, the recovered metals can be estimated. Empirical datasets on e-waste decomposition will be available to link to the deep learning models [41].

The value calculation will provide supplementary knowledge to remanufactures and will guide them in identifying the proper end-of-use (EoU) fate for each device. Although there is a wide disparity between product segments and brand-to-brand, aggregate data provides baselines for the most widely used materials in consumer electronics. For example, most electronics include casings, circuit boards, wiring, and glass. 25% of mobile devices and up to 50% of larger computer equipment are made up of plastic or metal casings [42]. The printed circuit boards include 28% metal and 72% non-metallic materials [43]. Metals in WEEE can be broadly categorized as base or commodity metals, precious metals, specialty metals and metalloids, and hazardous metals [44]. The current aggregate data on e-waste composition and life cycle assessment studies help us develop databases needed to be integrated into AI tools for economic and environmental evaluation. Examples of such studies are [45], [46].

3.3 Step 3: Develop remanufacturing recommender systems

Recommender systems are valuable tools that have been widely used to provide users with product or service recommendations (e.g., movie, music, product, book suggestions). Due to their popularity, various techniques have been developed for recommender systems. Examples are data mining techniques, content-based algorithms, neighborhood-based methods, collaborative filtering, constraint-based recommendation, and context-aware recommendation systems [47].

Recently, the application of deep learning techniques has become a trending topic, particularly for content-based recommenders [48], [49]. The concept of recommender systems has not been developed for remanufacturing systems, particularly considering the existing inherent variability and uncertainty in the waste stream. This step leverages deep learning-based algorithms to produce recommendations based on features and latent factors extracted from Transfromer-CNNs developed in Step 1. Deep learning will be used for automatic feature learning from product images and creating corresponding inputs for content-based filtering.

The proposed algorithms consist of two main stages: (1) use CNN architectures to automatically extract teardown features (e.g., device type, type of fasteners, number of modules, type of cables, part size, part color) and (2) develop clustering algorithms to group items based on similarities in their features and suggest a set of recommendations for product clusters using content-based filtering and knowledge-based filtering approaches.

Figure 4 shows a simple example of the proposed clustering-based method. It includes several steps i) a pre-processing unit that performs frame quality check and image normalization, ii) the K-Means clustering technique to ensure the same brand of products falls into the same clusters, iii) efficient feature descriptors that encode intra-class variations at an optimal cost at the intermediate stage, and iv) complex descriptors and modeling at the final stage.

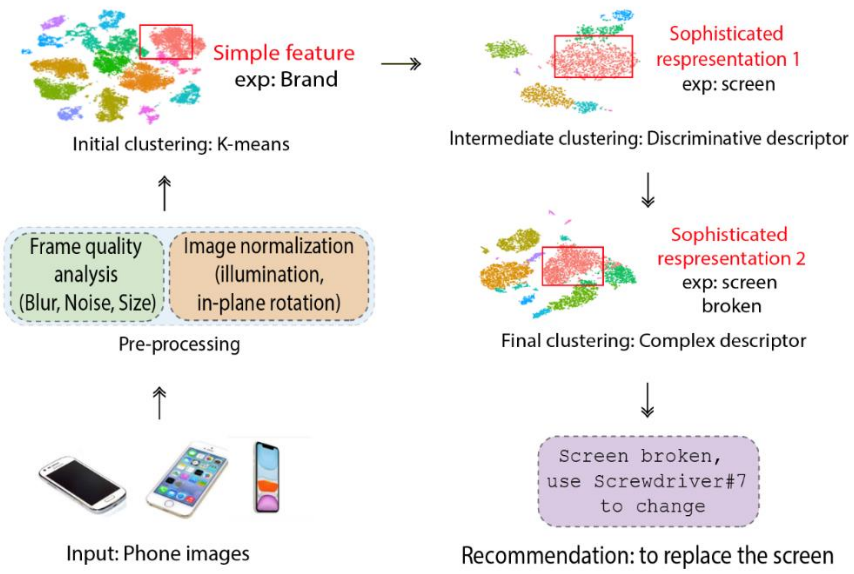

Fig. 4. The clustering-based approach for identifying EoU decisions for product clusters

It should be noted that suggesting the recovery option for each product cluster depends on many internal and external factors specific to each remanufacturing site (e.g., capacity, available infrastructure, market price, and environmental regulations). While accessing real-world historical data from remanufacturing sites on the rating of the EoU option for each device is challenging, available literature and the data sets can be used as a source for forming a base dataset for analysis.

4 Applications of AI-driven Value Assessment Framework

Intelligent detection solutions can be used to effectively extract product composition data and provide insights into the value still embedded in them. The term "value" refers to various aspects such as material decomposition of the product, critical raw materials, precious metals and plastics, toxic and hazardous parts, price in the secondhand market, future reusability based on the technology level, lifecycle assessment outcomes, and embodied energy from component production, to name a few.

The learned features from product teardown images can be connected to databases collected from experimental studies and data available in the literature that help with value estimation. For example, the amount of critical raw materials available for recovery from a particular computer notebook can be computed from images of lithium-ion batteries (e.g., cobalt) and hard disk drives (e.g., dysprosium and neodymium). Information such as market characteristics and composition of major components provides a baseline for creating such databases.

This section elaborates on several applications of the proposed AI-guided product assessment framework.

4.1 Improved Value Assessment in Trade-In Programs

Trade-in programs offer consumers financial incentives in exchange for returning their used products. An extensive number of trade-in programs are available nationwide. Examples are Amazon Trade-In, Apple Take-back, Best Buy Trade-In, Nextworth, Gazelle, ReCellular, eBay Instant Sale, Flipsy.com, and University bookstores. They vary in performance in terms of the convenience of collection method, the monetary incentives they offer to consumers, and the type of product design features they pay attention to, e.g., power on/off, display condition, disabled activation lock, memory size, and phone carrier.

Consumers often submit information about their products to online trade-in programs. Based on the information submitted by consumers, the take-back program offers them a price. One challenge facing take-back systems is the lack of a common language between consumers and retailers on the cosmetic condition of used devices. Most trade-in programs offer broad classifications of the device concerning its physical condition, e.g., broken, good, and flawless. The variation in understanding the cosmetic condition and incorrect interpretation by consumers may lead to a difference in the expected price and price quote received after inspection by the trade-in company. The probability of consumer participation in these programs depends on several factors such as the price offered, the convenience, the user-friendly website, and easy-to-understand questions. Equipping trade-in programs with AI technology will strengthen their effectiveness compared to conventional recovery methods.

Jayaram et al. conducted a preliminary analysis of various trade-in programs available for cell phones in the US [50]. The goal was to determine the factors that influence the product trade-in price. The case study was restricted to a single product and OEM (Apple). Seven cell phone trade-in programs of the following types have been studied: Phone network operators, online retailers, recyclers, and educational institutions. Each program offers incentives such as gift coupons, store credit, or cash for trading in cell phones. The most significant factors of a cell phone trade-in program were the following factors: OEM of cell phone, age, memory size, cellphone model, conditions, and phone network carrier. Interestingly enough, a considerable number of these characteristics can be visually extracted from product images, making our proposed framework compatible with the needs of trade-in programs.

4.2 Identify Proper Recovery Operations for Product Clusters

The physical inspection of the product may facilitate identifying the appropriate recovery options, required operations, tools, and resources based on the device design configurations. For example, suppose remanufacturers define reusability indexes based on physical product conditions and the secondhand market potential. The image recognition solutions integrated with recommendation algorithms help them physically inspect products in real-time, automatically compute the reusability, and cluster products.

A big portion of electronics that e-waste recovery facilities receive (for example, from state agencies, organizations, and school boards) have the potential for remanufacturing. While the recovery sites, particularly R2-certified facilities, have to meet several quality checks besides just visual inspection, "a high percentage" of devices are judged (at least at some important step) based on visual inspection. The portion of e-waste that is not even a candidate for remanufacturing still needs to be disassembled as part of the recycling process. For example, flat-screen TVs/monitors are disassembled into base components (plastic, steel, screens), and each is shipped off. Therefore, the analysis at teardown levels is needed to identify the necessary remanufacturing tools and procedures.

The teardown features extracted from image processing techniques help in identifying feasible recovery solutions. Identifying the type of fasters, joint parts, standard components, overlapping parts, degree of modularity, and the number of parts are examples of features that can be extracted using object detection technology.

4.3 Case Study: Screw Detection and Tools Recommendation

Providing detailed case studies is beyond the scope of this concept paper; however, to clarify the application of the proposed framework, we briefly summarize a relevant study conducted by Zhang et al [51].

The study presents a framework to automate screw detection and tool recommendation for robotic-assisted disassembly of end-of-use electronics. The objective is to address challenges in detecting small objects such as screws and fasteners widespread in electronics. The framework consists of two modules: (1) a target detection module using YOLOv4 and (2) a tool recommendation module based on EfficientNetV2. The YOLOv4 model is optimized by modifying the backbone network, specifically by using low-level semantic information and cutting redundant connections to improve detection accuracy for small objects. The screw detection results are then classified by the EfficientNetV2 model.

To evaluate performance, the authors tested the system using a dataset of 300 images containing three screw types (Torx security, Phillips, and Pentalobe). The optimized YOLOv4 model achieved a mean average precision (mAP) of 0.9424, demonstrating improved detection accuracy compared to the baseline model. For tool recommendation, three models were tested: a simple classification model (M-3c), a classification model with false detection handling (M-4c), and a model incorporating data augmentation (M-4c-aug). The final model (M-4c-aug) achieved an average F1-score of 99.28%, with improved classification results for all screw types. The results show that combining computer vision techniques such as YOLOv4 and EfficientNetV2 can detect screws and recommend tools for robotic disassembly. For more information, we refer readers to Zhang et al [51][52].

5 Conclusion

The paper discusses the scientific foundations for providing digital assistant systems to the remanufacturing workforce for handling the inherent variability in e-waste streams. A computational framework has been proposed to facilitate automated classification and assessment of products through vision-based value quantification and recovery recommendation. The work will advance object detection and semantic segmentation techniques to convert product images and teardown pictures into a discrete form that permits quantitative characterization of product features and subsequent feasibility modeling of recycling decisions. The paper discusses the importance of developing image processing techniques for detecting small and overlapping parts expected in consumer electronics design. The segmentation algorithms represent fully automated deep learning systems and a set of recommender algorithms to cluster products and suggest the best recovery fate for each cluster based on its profile and similarity to previously recycled items.

The paper can be extended in several ways. First, the proposed framework should be implemented and evaluated in practice through a cohesive data collection of consumer electronics images. Further, the application of the proposed framework in developing other sustainability metrics such as repairability, disassembleability, and recyclability can be discussed.

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