Electronic waste Footprint of Computer Systems

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Abstract

Modern computer systems have an unprecedented environmental impact in the form of electronic waste at the end-of-life. Computer systems contain several hazardous materials whose improper disposal can lead to detrimental ecological and public health impacts due to their embodied toxicity. In this paper, we focus on developing methodologies to quantify the component-wise makeup of computer systems and assess their toxicity impact to inform more sustainable design choices.

1 Introduction

In today's digital age, computer systems have become indispensable tools facilitating everything from global connectivity and entertainment to everyday tasks. However, the widespread adoption of technological devices coupled with the rapid pace of innovation has led to a significant growth in the annual production volume of such products, which has consequently given rise to an enormous electronic waste problem.

The ever-increasing amount of electronic waste has become a global environmental issue [11]. As of 2019, more than 50 million metric tons of e-waste was generated worldwide [7], of which only 17.4% was formally collected and recycled while the rest is eventually landfilled or incinerated. Electronic devices like computer systems contain a multitude of hazardous materials, including metals and organic compounds [5]. Improper disposal of these devices at the end-of-life can result in significant harm to both the environment and human well-being.

Addressing the e-waste problem requires a multifaceted approach, one in which system designers play a pivotal role by implementing sustainable design practices, such as creating modular systems for easier recycling, prolonging product lifetimes, and minimizing the use of hazardous materials in system components. However, to attain this objective, it is crucial to first quantify the environmental and human health repercussions of e-waste generated by computer systems at the end-of-life. By doing so, we can pinpoint the most hazardous components and devise strategies to minimize or eliminate their usage.

Measuring the e-waste impact of computer systems is a challenge owing to the lack of information on the quantity or dimensions of different components utilized in its assembly. Additionally, the material composition of these components is also not public information. In this paper, we focus on tackling the first challenge by formulating approaches to quantify the variety of components present in computer systems leveraging image recognition and object detection strategies.

2 Background

More than 80% of e-waste is improperly handled and ends up being landfilled or incinerated [7, 18]. Around 7-20% of e-waste generated in developed countries travels transboundary to low- and middle-income countries [7]. About 80% of the e-waste that is sent for recycling in developed countries also meets the same fate [16]. As a result, all this e-waste ends up in developing world, which lacks the proper infrastructure for recycling, leading to e-waste being handled informally [2].

Informal recycling of e-waste exposes workers to hazardous substances that can lead to both cancerous and non-cancerous diseases [10, 16]. Not only the workers but everyone who lives near an informal facility gets chronically exposed to pollutants through inhalation or contaminated food and water supply. The ill effects of e-waste eventually make their way to humans and various other species who live farther away by ultimately contaminating the food chain and drinking water [2, 16]. Thus, the hazardous chemicals present in e-waste make it a huge safety risk both for human health and the environment.

Modern computer systems contain more than 60 elements from the periodic table [12]. Several metals utilized in computer systems, like lead, mercury, arsenic, and nickel are extremely detrimental for human health and the environment [10, 14]. Certain organic compounds like brominated flame-retardants and Polyvinyl Chloride (PVC), are also extremely harmful to humans [10]. Further, the plastics present in e-waste are responsible for GreenHouse Gas (GHG) emissions [20]. Computer systems also utilize conflict minerals (gold, tin, tantalum, tungsten), which are responsible for perpetuating social and humanitarian issues [3]. As a result, computer systems have a manifold detrimental impact on both human well-being and the environment when improperly handled at end-of-life.

3 E-waste Footprint

Computer systems encompass many components with different structures and functionalities, ranging from the Printed Circuit Board (PCB), processors, memory modules, and storage devices to components like casing, display, cooling elements such as fans, and batteries in battery-powered devices.

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Some components, like the PCB and processors, further comprise different active components like amplifiers and transistors, as well as passive components, such as resistors and capacitors. Computer systems like smartphones, laptops, PCs, and servers comprise these components in varying sizes and material compositions.

With respect to material composition, various components of computer systems exhibit distinct characteristics. Batteries and PCBs have the highest fraction of metals by weight in computing devices [17]. PCBs also harbor the highest diversity of metals and their compounds in a computer system [4], owing to various components present on the PCB, like resistors, capacitors, and integrated circuits. The displays and touchscreen in smartphones can contain several rare-earth metals [1]. Processors and memory systems contain precious metals like gold and silver [6]. The composition of different components influences the overall toxicity footprint of a computer system at the end of its lifetime.

Accurately assessing the toxicity footprint of a computer system requires knowledge of the dimensions and quantities of each component present in the system, along with their material compositions. For instance, we need information about the number of integrated circuits on the PCB of a laptop and the material makeup to determine their proportionate contribution in the overall toxicity impact of the laptop. Similarly, the dimensions of the display of a smartphone, along with material composition, are required to calculate its toxicity impact.

In this work, we develop object detection techniques to identify and enumerate various components within a computer system, ultimately enabling the assessment of the toxicity impact associated with these systems. Furthermore, the precise localization of different components utilizing these techniques can significantly improve recycling efforts leading to better e-waste management.

4 Methodology

In this section, we outline our methodology for designing the pipeline to identify and count different components of a computer system using object detection techniques. We focus our discussion on components present on the PCBs of computer systems, owing to their diversity and density. Nonetheless, a similar approach can be extended to other components of computer systems like displays, processors, memory, and so on.

4.1 Dataset

To utilize object detection techniques for component identification, we require a dataset of high-resolution PCB images. Only a handful of public datasets of PCB images exist [13, 15], collected primarily for quality assurance. These datasets also do not necessarily contain the labels of various components or PCBs images of servers, smartphones, or PCs.

As a result, we collect our own dataset of high-resolution PCB images sourced from the internet. Our dataset comprises 54 images of PCBs from servers, smartphones, and PCs. We manually label PCB components from 5 component classes, namely resistors, large capacitors, small capacitors, inductors, and integrated circuits. Currently, we do not distinguish between different components of the same component class. For instance, all surface-mount resistors with different sizes and ratings belong to the same component class. We partition the dataset into training, validation, and testing sets using a 70-10-20 ratio.

4.2 Object Detection for Component Identification

We leverage state-of-the-art object detection algorithms for component identification, namely - RCNN [9], Fast-RCNN [8] and YOLO [19]. Object detection algorithms identify the components and classify them into relevant component classes. We also utilize this information to count the number of components detected for each class.

4.3 Evaluation

We evaluate the accuracy of object detection algorithms using Mean Average Precision (mAP), Precision, and Recall metrics. Further, we also calculate the difference between the actual count and the detected count for components of each class.

5 Further Work

Numerous avenues for improvement exist in the component identification and enumeration pipeline. First, our dataset is relatively small and we consider a limited number of component classes. Second, the object detection algorithm for component classification is challenging to implement with high accuracy due to several reasons. For instance - the small size of components like resistors can make them hard to detect, and the size and density of the components of the same class can vary significantly across PCBs. To address these challenges, we intend to increase the size of our dataset, as well as refine the object detection algorithm to enhance accuracy.

Further, we plan to expand the methodology to incorporate other components of computer systems like displays, casing, memory and storage devices. For instance, we can calculate the size of smartphone displays using object localization and dimension detection techniques.

Finally, utilizing our model and information about material composition of components of interest in a computer system, we can calculate their environmental and human health toxicity impact at the end-of-life - which is crucial to inform sustainable design decisions and improved e-waste management practices.

References

[1] Apple_material_impact_profiles_paper_2019_release final from bwd-updated.pages. https://www.apple.com/environment/pdf/Apple_Material_Impact_Profiles_April2019.pdf. (Accessed on 10/24/2023).

[2] Michelle Allsopp, David Santillo, and Paul Johnston. Environmental and human health concerns in the processing of electrical and electronic waste. *UK: Greenpeace Research Laboratories, Department of Biological Sciences, University of Exeter, Exeter*, 2006.

[3] Bali Barume, Uwe Naeher, Désirée Ruppen, and Philip Schütte. Conflict minerals (3tg): Mining production, applications and recycling. *Current Opinion in Green and Sustainable Chemistry*, 1:8–12, 2016.

[4] Waldir A Bizzo, Renata A Figueiredo, and Valdelis F De Andrade. Characterization of printed circuit boards for metal and energy recovery after milling and mechanical separation. *Materials*, 7(6):4555–4566, 2014.

[5] Kevin Brigden, Joe Webster, Iryna Labunska, and David Santillo. Toxic chemicals in computers reloaded. *Greenpeace-Research Laboratories Technical note*, 6(07), 2007.

[6] MIT Green Computing. Computers and environment. https://web.mit.edu/ieee/sanjay/11.122/ewaste.htm.

[7] Vanessa Forti, Cornelis P Balde, Ruediger Kuehr, and Garam Bel. The global e-waste monitor 2020: Quantities, flows and the circular economy potential. 2020.

[8] Ross Girshick. Fast r-cnn, 2015.

[9] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation, 2014.

[10] Kristen Grant, Fiona C Goldizen, Peter D Sly, Marie-Noel Brune, Maria Neira, Martin van den Berg, and Rosana E Norman. Health consequences of exposure to e-waste: a systematic review. *The lancet global health*, 1(6):e350–e361, 2013.

[11] Michelle Heacock, Carol Bain Kelly, Kwadwo Ansong Asante, Linda S Birnbaum, Åke Lennart Bergman, Marie-Noel Bruné, Irena Buka, David O Carpenter, Aimin Chen, Xia Huo, et al. E-waste and harm to vulnerable populations: a growing global problem. *Environmental health perspectives*, 124(5):550–555, 2016.

[12] Elizabeth Jardim. From smart to senseless: The global impact of 10 years of smartphones. *Greenpeace Inc.: Washington, DC, USA*, 2017.

[13] Nathan Jessurun, Olivia P Dizon-Paradis, Jacob Harrison, Shajib Ghosh, Mark M Tehranipoor, Damon L Woodard, and Navid Asadizanjani. Fpic: a novel semantic dataset for optical pcb assurance. *ACM Journal on Emerging Technologies in Computing Systems*, 19(2):1–21, 2023.

[14] Charles Kofi Klutse, Mustapha Abeiku Quayson, Amos Forson, Christian Nuveadenu, and Ebenezer Aquisman Asare. Ecotoxicity of heavy metals in soil around long-term e-waste recycling sites in tema and ashaiman areas of ghana. 2023.

[15] Chia-Wen Kuo, Jacob D Ashmore, David Huggins, and Zsolt Kira. Data-efficient graph embedding learning for pcb component detection. In *2019 IEEE winter conference on applications of computer vision (WACV)*, pages 551–560. IEEE, 2019.

[16] Karin Lundgren. *The global impact of e-waste: addressing the challenge*. International Labour Organization, 2012.

[17] Mining.com. A breakdown of the critical metals in a smartphone. https://www.mining.com/web/a-breakdown-of-the-critical-metals-in-a-smartphone/.

[18] Keshav Parajuly, Ruediger Kuehr, Abhishek Kumar Awasthi, Colin Fitzpatrick, Josh Lepawsky, Elisabeth Smith, Rolf Widmer, and Xianlai Zeng. Future e-waste scenarios. 2019.

[19] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection, 2016.

[20] Paul Stegmann, Vassilis Daioglou, Marc Londo, Detlef P van Vuuren, and Martin Junginger. Plastic futures and their co2 emissions. *Nature*, 612(7939):272–276, 2022.