E-Waste Recycling Gets Smarter with Digitalization

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***Abstract*—Many of us have defective electrical devices in storerooms or drawers. Recycling electrical and electronic waste (E-waste) allows for reusing the original materials rather than mining new ones, especially if they are considered Rare Earth Elements. It is critical to separate and sort E-waste before recycling, which can be economically viable for products containing valuable metals and materials. Identification of the device and all related information will greatly support pre-dismantling. This work proposes a pipeline and automated system to identify the device using several techniques: artificial intelligence for device classification into device type, brand and model, multi-sensors for identifying internal components like Infrared or X-ray, a web crawler for creating image datasets using keywords from search engines, and a web scraper for retrieving device specifications, like dimensions, battery type, visual data, available colours, etc.**

***Index Terms*—E-waste, artificial intelligence, transfer learning, web crawler, web scrapper, multi-sensors**

I. Introduction

E-waste contains valuable materials such as gold, silver, aluminum, copper, cobalt, etc. But also, hazardous substances [1]. They are certainly not suitable for conventional recycling methods like shredding or melting. In addition, the business models of smartphone (for example) manufacturers and mobile phone providers are helping the mountain of discarded devices to grow steadily. This is due to the short life-cycle, almost two years. These challenges have a devastating impact on health and the environment. A study by [2] shows that there are over 5 billion smartphones that need to be recycled in 2022, and if these smartphones have 9 mm depth on average and are stacked flat on top of each other they would rise roughly $50,000$ km, almost one-eighth of the way to the moon.

Automated recycling systems have many advantages, including increasing the recovery rate and reducing the use of raw materials, managing waste in a sustainable and environmentally sound manner, and promoting circular economy processes for the benefit of society and industrial growth [3].

This work is organized as a presentation of related works in section II, then describing the suggested method in section III by showing the building blocks of the system, as the eyes III-A, the brain III-B with demonstration of device specification III-C1.

II. Related work

Materials Recovery Facilities (MRFs) face challenges due to the growing consumption per person. Therefore, combining vision-based systems with robots can tackle this problem since they run tirelessly 24/7 and can be faster and more accurate than expert human-based sorting systems if they are designed smartly, for example involving artificial intelligence. Recently, many attempts have been made to implement this concept. Using the ZenRobotics system, the Norwegian waste service operated the country's first municipal AI-robotic waste sorting station in 2021. United Kingdom announced a collaboration between Coventry City and Machinex to recycle $175,000$ tonnes per year. In France, the Veolia Group upgraded their sorting robot systems to implement AI towards achieving smarter sorting using six SamurAI sorting machines [4]. Texas-based waste management systems deployed 24 Artificial Intelligence (AI)-guided robotics solutions from AMP Robotics in 2020.

AMP is the world's pioneer and largest dataset of recyclable material images for use in machine learning that supports recycling businesses and producers to maximize recovery. Digitalization support systems are used in waste sorting on many different platforms. The AMP Neuron AI platform continuously trains itself by recognizing 50 billion packaging types in different colours, textures, shapes, sizes, patterns, and even brand labels. This is to identify materials and their recyclability. The robots use this intelligent system to pick up and place materials to be recycled with superior speed and accuracy than humans. The AMP Cortex provides high-speed robotics to automate the identification and sorting of recyclables from mixed material streams. The AMP Clarity provides data and material characterization on what recyclables are captured and missed [5].

A worth mentioned study by [6] designed a sorting robot for recycling by identifying the location based on a vision system. The robot grabs the object with its mechanical arm and places it in the corresponding bin. The system consists of an FPGA development kit, robot arm, ultrasonic module, lidar, three Omni wheels, and UP2 Board. Then the FPGA kit represents the main component that recognizes the obtained images from the HTTP server, avoids collisions by using lidar and ultrasonic modules, controls DC motors and Omni wheels to move the robot in all directions, controls the 3-axis robotic arm to pick up objects and place them in the corresponding recycling bin. The functionality of the system is as follows: The system recognizes bottles based on depth images. The depth images are acquired using a 3D camera connected to a UP2 board via a universal serial bus (USB) interface. An HTTP server is established on the UP2 board. The depth images of the bottle are captured and stored on the server.

III. Methods: Build a modular automated device identification

Recovered materials have various ranges of quality and value, therefore product classification (or sorting) is a fundamental task in the recycling process. Expert labour could perform the task manually. However, they are exposed to hazardous materials which lead to negative health impacts, especially in E-waste recycling. Digitization appears to be the best solution to automate the process in this scenario [7]. To overcome the previous challenges, a smart system is needed. A system that has ”eyes-brain-muscle” can be adapted to tackle the problem, as suggested in the building blocks in figure 1.

- **Eyes** can be RGB sensors to visualize the status of the device, and Infrared (IR)/X-ray sensors to detect information about the internal components of the device.
- A **brain** that is represented by an Artificial Intelligence (AI) system design that analyses images, makes decisions, and gives orders to dismantle.
- **Muscles** could be represented by robot arms to disassemble the device. This automated system processes E-waste recycling on a conveyor belt with minimal human interaction.

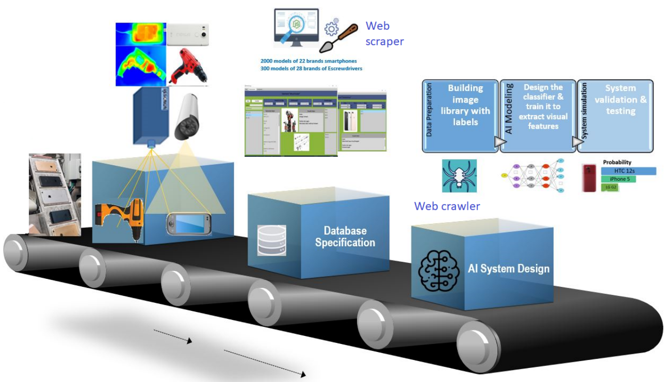

Fig. 1. The suggested digitalization approach.

The system architecture is as follows: the device is placed on the conveyor belt, then passed to the photo box equipped with RGB cameras from different angles to provide a multi-viewpoint of the device and improve classification accuracy. To classify the device, the images acquired by the RGB cameras are processed by a deep learning algorithm trained on a dataset created using a web crawler. Once the device is recognized, all the corresponding information stored in the datasheet is stored in a database that is retrieved using a web scraper. When a device is classified, no further steps need to be taken, such as X-ray or IR image acquisition, and it can proceed directly to the final dismantling phase. During the first treatment, the device is heated under an infrared lamp, and an infrared camera shows the variance in the temperature contrasts of the internal components. A supporting X-ray booth that shows further detailed information about the internal elements can also be installed on the conveyor belt.

A. *Using multi sensors*

The multi sensor method is applied in many fields to share the advantages of sensors in different light spectra to maximize information and minimize redundancy. Deep Learning has demonstrated its efficiency in processing the RGB colour space with high precision. However, these images process features in the visual spectrum. Multiple sensors **(eyes)** could be used to detect a broader range of materials to be recycled. This detection can be achieved with a variety of sensors in the visual and non-visual spectrum. Our previous study [8], shows in further details, how Infrared (IR) imagery is used to detect temperature contrasts to distinguish internal components like the battery, the lenses, and the fingerprint sensor of the smartphone. In addition, the motor, the battery, and the head of the electric screwdriver. Besides, IR sensors are safe, cost-effective, and suitable for defining the location and composition of internal materials. The IR radiator is suggested because of its many advantages, including its high disassembly rate, suitability for small volumes, and relatively low damage ratio for the electrical component. Moreover, our previous study [9] also shows the potential to process X-ray images with transfer learning to predict whether the image contains a battery or not, in localization, and in identifying three types of batteries, namely: prismatic, flat, and cylindrical lithium-ion batteries (LIB).

B. *AI system design*

To enable recycle old electrical devices automatically and efficiently, it is critical to identify the product model. Only knowledge of product characteristics makes it possible to disassemble the devices in such a way that valuable raw materials, but also pollutants, can be collected separately. Using AI to classify the models is another method that has been successful with the transfer learning approach [10]. More specifically, the **(brain)** processes the acquired images and uses deep learning methods to sort (classify) the device type, manufacturer, and model (e.g., smart phone, Apple, iPhone 6). The electrical device that needs to be recycled is placed on the conveyor belt. It is then passed to a photo box that takes photos from different angles, as shown in figure 2. These images are processed by the brain that implements deep learning to classify the device. As a brain, AI identifies the repetitive patterns in E-waste. This is done by training large amounts of data for patterns and structures and recognizing correlations and differences between the features of the image. To sort the devices, the classifier uses the previously stored images in the training set to train the deep learning classification algorithm. These images can be obtained from search engines using a web crawler, then manually filtered to remove noisy images. Next, the brain validates the testing device (that needs to be recycled) in real-time. The details of the implementation of AI classifier with the web crawler is described with technical details comprehensively in our previous work [11], besides, all details about designing the AI algorithm for the classifier to sort new devices with the transfer learning technique are described along with the results demonstration. In addition, the study describes, how to apply what was learned to new object classes based on a few samples. Once the device has been classified into type, brand, and model number, further specifications are retrieved from online databases that store device characteristics. All data required for the next step will be transferred to the robot system **(muscles)** via a Modbus protocol, for example.

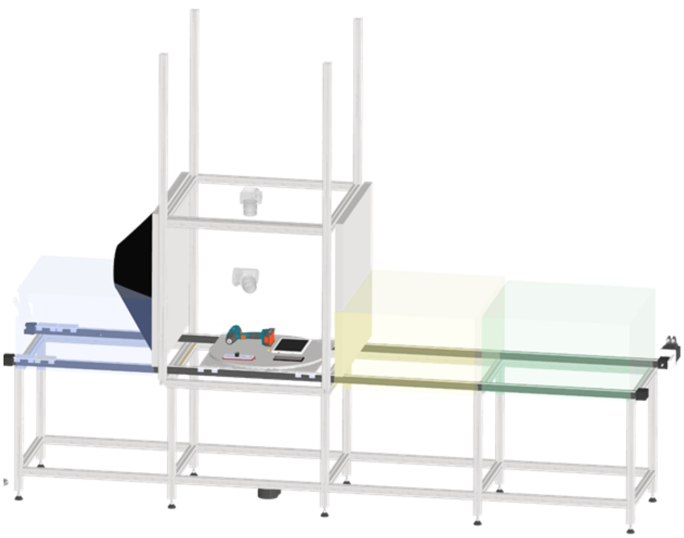

Fig. 2. The setting of the photo box on the conveyor belt

C. Creating a database for object specifications

The specifications about the E-waste, such as the dimensions, battery specifications, and list of internal components, will serve as a guide to chemical and material treatment later. As mentioned in section III-A, all the information included in the datasheet of a device could support the identification of electrical components and enhance the recycling process as a whole. Therefore, we need a solution to extract this data accurately and easily. Our approach suggested that web scraping is a suitable technique to tackle this problem.

1) Web scraping: Web scraping is the technique of extracting data from the web and presenting it in the desired format using a script or a program [12]. It is an efficient technique because it saves the information in a database or a file for later analysis. Since it is simple to automate, it is ideal for online price comparison, monitoring weather conditions, and detecting changes on the web [13]. Web scrapers allow the user to gather much data quickly and easily, which would consume much time manually. When the scraper opens a link, it collects the raw data of the website. The source web page could be written in different formats: HTML, XML, JSON, or multimedia data like images, videos, etc. [14]. The extractor needs to be exactly defined, so it can handle all this information.
To implement this approach, a database containing as much information about the devices is required. The data is retrieved by browsing a specific website and collecting the device datasheet. The images related to the device are also stored in a separate folder. We then need to deliver this information to the next phase of recycling in an easily accessible Graphical User Interface (GUI). To do this, we use MATLAB to scrap the information from specific websites.

2) Implementing web scrapping: We find that "www.gsmarena.com" [15]and "www.akkuschrauber.com" [16] are suitable sources to scrap data for smartphones and electric screwdrivers, respectively. A web scraper should start by acquiring the web page source and finding out where the data is stored. Then, implementing the web scrapper for both smartphones, as shown in figure 3 and screwdrivers, as shown in figure 4, in MATLAB is performed as:

Algorithm 1: Web scrapping Pseudocode.

Data: S ← Start of the page
E ← End of the page
U ← Specific URL
V ← Name of device
Result: Extract related substrings and images
E ← $< /td >$ a command that ends HTML page
if *the recycled device has a suitable website to scrap from* **then**
  1) HTTP Request to U
  2) Read U using *"Webread"*
  3) Store the source code of U
  4) Extract all data by retrieving all substrings between S and E using *"ExtracBetween"*
  5) Parse and organize all substrings in specifications fields related to V
  6) Extract the images from U and saves them as 3D Matrices
  if *a specification of V is missing* **then**
    Fill manually
  end if
else
  Web crawler is used to download the related URLs
end if

A web scraper stores all information related to the brand, model number, dimensions, power, release date, battery type, available colours, etc. in a database. It collects 2000 models of 22 brands of smartphones and 300 models of 28 brands of electric screwdrivers automatically.

Web scraping is a powerful technique. However, it could have legal concerns related to copyright. Downloading and using the data for non-commercial purposes is permitted by the terms of use [17]. A reasonable query should be executed frequently to prevent blocking access [18].

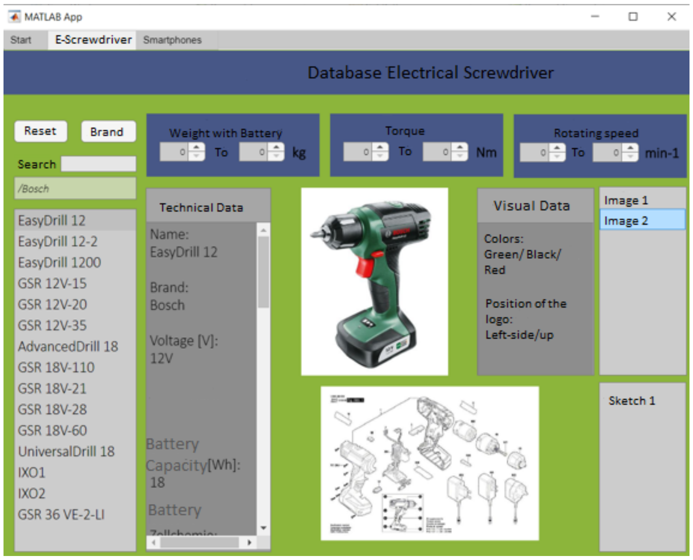

Fig. 3. The graphical user interface of electric screwdriver specifications.

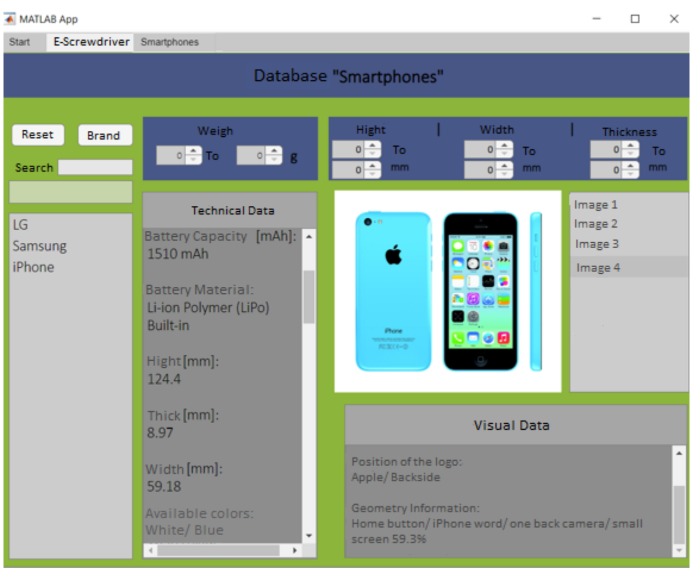

Fig. 4. The graphical user interface of smartphones specifications.

IV. Conclusion

The transition to this system moves the staff to play roles in maintenance, equipment operator, route drivers etc, instead of having direct contact with waste streams.

A novel approach for supporting the automation of recycling E-waste has been proposed in detail in this work. This system is designed as follows: A photo box collects RGB images on the conveyor belt to classify them using a transfer learning method trained on images retrieved by a web crawler. Using a web scraper, a database retrieves all information related to this device from a specific website. Following this, the device is heated under an IR lamp in order to detect internal components by analyzing the temperature difference. An X-ray device could also be installed for a more detailed material reveal. The benefits in the cost reduction, and the approximate cost of the suggested system can be presented in future work.

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