An Approach for Smart and cost-Efficient Automated E-Waste Recycling for Small to medium-Sized Devices Using multi-Sensors

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***Abstract*—Recycling electrical and electronic devices in an automated method can reduce the negative impact on human health and the environment compared with manual dismantling. This approach suggests using multi-sensors by using RGB sensor to classify the devices using a deep learning method and infrared sensor to recognize the internal component of the device. Particularly, the sorting accuracy achieves 98.5% using the state-of-the-art EfficientNet for the tested devices, and infrared images give a significant guide to the main components of the devices. Eventually, this information can be transferred to the next stage of material processing to provide fewer risks and a smarter way to avoid toxic materials.**

***Index Terms*—Mult-sensor, E-Waste recycling, Infrared sensor, transfer learning.**

I. Introduction

The multi-sensors method is widely applied to take the advantages of sensors in different ranges of the light spectrum together to maximize meaningful information and minimize redundancy [1]. Deep learning proves its efficiency in processing RGB color space with high accuracy. However, these images exhibit features in the visible spectrum. Infrared (IR) images are used in detecting the contrast of temperature, and they are safe, cost-effective, and convenient in different applications, such as preventative maintenance [2], security inspections, gas detection, anomalies detection [3], etc.

II. Related work

Many initiatives support the automation of the recycling process, in general, using different sensors.
ZenRobotics uses a combination of artificial intelligence (AI), robots and Near InfraRed (NIR) sensors to sort 13 different materials with an accuracy of 97% [4], namely: Ferrous metals, non-ferrous metals, textiles, cardboard, wood, paper, High Density Polyethylene (HDPE), Low Density Polyethylene (LDPE), PolyPropylene (PP), PolyEthylene Terephthalate (PET), other mixed plastics, Tetra Pak, printing, and green waste. This robot has an average purity 97% for tested waste streams. The study emphasizes the importance of digitalization as an "instrument" for achieving sustainability and future competitiveness efforts.
Fujitsu uses signal and image processing combined with deep learning to inspect Non-Destructive Testing (NDT) techniques to detect patterns for manufacturing defects [5]. NDT could also be used to check for visible and invisible damages in the field of predictive maintenance before it turns into catastrophic failure, which is not always detected by available tools [6]. Nonetheless, to be of our knowledge, there is no study about the automation of recycling electrical and electronic devices or the so-called E-Waste.
Maurice et al. [7] conducted a qualitative study of 13 metal recycling methods, including manual dismantling, surface cutting knife, hot air heating, and InfraRed radiators, for example. It was concluded in this study that no single method would be sufficient to solve the problem since each method possessed strengths and weaknesses. Therefore, a combination of them could achieve higher accuracy and reduce the limitations of using one method. Although manual dismantling has cheap CAPital EXpenses (CAPEX), provides selective disassembling, and is easy to implement, it has very expensive OPerating EXpenses (OPEX), and is a polluting, slow process and requires hard-manual work and manpower. Based on their research, the authors concluded that IR radiations have moderate CAPEX and low OPEX costs. This makes them a feasible solution as they allow for easy disassembly and can fit small volumes of devices.

III. The suggested approach: Using multiple sensors

Based on previous related work in section II, and the growing need to automate the process of recycling E-Waste this approach aims to apply multiple sensors to detect a wider range of materials needed to be recycled. This detection can be achieved through a variety of sensors ranging between the visible and invisible spectrum. The RGB camera or sensor can be supplemented by other sensors to support extracting ECs.

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The objective here is to define the location and composition of the internal materials with minimal human intervention. In addition, IR is used to detect the location and characteristics of the internal components of Ewaste.

A. Test setups

This test used active thermography to analyze the main components of the device. To make the internal features visible to the surface IR lamp Trotec IR S2550 is used to heat up the devices to around 50° with a heating capacity of 2500W, and it is positioned 1m on top of the device. The IR camera, FLIR T1030sc is placed about 1m in front of the heated device. For the RGB images, a Mako G-419C color camera is used to acquire images for the tested devices that need to be sorted.

B. Using an infrared sensor

This approach suggests using an IR imaging system to detect the thermal contrast between the internal components to recognize them. The emission of IR energy can be used to distinguish the contrast of these objects with the background and their emissivity. This technique is applied and found that the IR images could reveal the internal components of a smartphone "Samsung A20" and an electric screwdriver "Einhell TE-CD 18/50", for example. In Figure 1, significant features can be clearly seen as internal components, such as the battery, the lenses, and the fingerprint sensor of the smartphone. In addition, the motor, the battery, and the head of the electric screwdriver can also be clearly seen [8]. Assuming that comparing these findings with the datasheet of the device. It will make the detaching and disassembly of these individual components easier.

The IR radiator is suggested due to many advantages, like a high disassembly rate, suitable for small volumes, and the damage ratio of the electrical component (EC) is low [9]. Controlled IR radiators are one of the most advanced methods to reach solder to its melting point [10]. Once the solder melts, the internal components can be separated from the device by a robot vacuum gripper for example. Park and coworkers achieved 94% disassembly rate of electrical components using this method along with the automatic rotating rod and sweeping steel brush-type apparatus at an operating temperature of 250°C and feeding rate of 0.33 cm/s [11]. Another application for this technique is detaching small components. This method could also be used to de-solder electrical components at different temperatures without damaging them. This is due to the nature of small devices, like smartphones, which include small and closely aligned components. Therefore, the ECs will be detached and then gripped away with a robot or shearing machine.

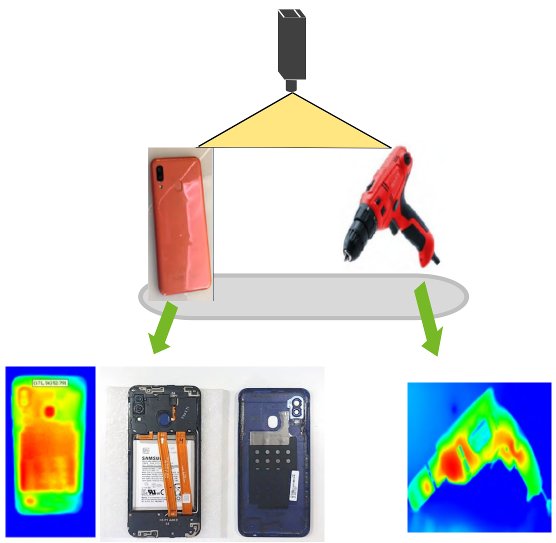

Fig. 1. Detecting the internal electrical components in a smartphone and electric screwdriver using infrared sensor.

C. Using an RGB sensor

This approach suggests using an RGB imaging system to classify devices into device type, brand, and model number. To apply this sorting method, the state-of-the-art deep learning method is used, which is the transfer learning technique. Simply, it applies the knowledge gained from completing one task to solve a different but related task [12]. This technique provides many advantages, such as reducing computational time, bringing high classification and recognition accuracy, being easier than building a neural network from scratch, and the ability to use a small dataset in order to achieve these advantages [13].

Another advantage of using artificial intelligence in E-Waste recycling is cost-effective. Objects can be classified optically using deep learning and can provide high accuracy while using only an RGB camera and a computer. A study by [14] shows that using an RGB images acquisition of tantalum capacitors recycling using automated selective dismantling is economically feasible and can provide 15% return of investment over four years. The study is implemented by training a convolutional neural network to detect these capacitors on the Printed Circuit Boards (PCB), then they are removed mechanically using a scrapper mounted on a robot arm. Hyperspectral images have several channels like IR channels can highlight metal traces and provide more information than RGB images. However, they have many challenges including insufficient labeled data for training, and the high volume of produced data [15].

Convolutional Neural Networks (CNN) are usually built at fixed resources, then they could be scaled up for better accuracy if resources allow. The scale is performed commonly by increasing the network depth (represented by the number of layers), width (represented by the number of filters or channels within each layer), or image resolution (represented by the number of pixels in the image). The study of [16] is the first empirical testing to trade-off these three factors. The suggested model was not designed rather it uses a multi-objective neural architecture search to create a baseline network and scale it up to obtain a family of models called EfficientNets, which is an optimization process that searches for the network architecture with the highest possible accuracy given at fixed computational

resources. It is as the name implies very computationally efficient and achieves 84.4% top-1 accuracy on ImageNet. It is the state-of-the-art of image classification that optimizes both accuracy and efficiency by measuring FLoating-point Operations Per Second (FLOPS) using the compound coefficient term to uniformly scale network width, depth, and resolution. It also transfers well to small datasets with fewer parameters than other popular CNN models.
EfficientNets use three tricks that are reasons behind the better accuracy and efficiency, namely, the inverted residual nets, swish activation function, and squeeze and excitation block, as follows:

- There are 7 inverted residual blocks, but their settings are different, so the trainable parameters are greatly reduced. In the residual block, depthwise separable convolution is used, which is depthwise convolution first followed by pointwise convolution [17].
- Take advantage of the squeeze and excitation block. The output feature maps that are created by a convolutional layer usually give equal weightage to each channel. However, the squeeze and excitation block assigns weightage to each channel instead of treating them equally [18]
- As an activation function, the blocks use swish activation. This is a multiplication of a linear and a sigmoid activation and it is proven to achieve 0.6% more accuracy on the ImageNet dataset [19]

Our study used the frozen weights of EfficientNet B0 model for image classification. It is a mobile size architecture having 11M trainable parameters. The testing environment was MATLAB applied to NVIDIA GeForce RTX 3070 GPU with 20 epochs and 10^{-4} learning rate. The tested dataset is a balanced dataset that has a mix of RGB images that are collected from search engines. It consists of 7 classes of smartphones namely iPhone3, iPhone4, iPhone5, iPhone6, Huawei P20, Gigaset, Samsung A20, and 7 classes of electrical screwdrivers; Bosch GSR18V21, Bosch GSR12V15, Bosch GSB12V35, Bosch Easydrill1200, and Einhell TE-CD18/50. The validation accuracy achieves 98.5%, and figure 2 shows an example of classification accuracy of a subset of the tested devices. The figure shows that the tested model can differentiate between two very similar shape objects, which are iPhone3 and iPhone4 with about 97% accuracy.

D. Combining results

The previous discussion shows that each IR and RGB images have their strength and weakness. To tackle this challenge and respect cost efficiency, an ensemble of multi-sensors with deep learning can yield promising results. This approach proposes joining information collected from previous experiments, which are: The device type, brand, and model number from the RGB sensor, and identifying the exact location of internal components from the IR sensor, then sending them to robots, for example, for the next phase of material processing. This would help in achieving automated recycling with minimum human interventions and better recovery rates.

Fig. 2. Example of classification accuracy of a subset of the tested devices.

IV. Conclusion

This study suggests an approach for smart sorting small to medium-sized electrical and electronic devices using RGB images with transfer learning efficiently. In addition, it shows that internal components can be identified through IR sensors. A combination of these sensors provides a safe and cost-effective method to support the recycling process by deploying two types of sensors in a complementary way, namely RGB and IR images. RGB images can classify electrical devices (smartphones and electrical screwdrivers for case study) efficiently, whereas IR images can be used to distinguish the main components of devices with their locations. Future work aims to test more electrical devices and include more sensors like X-ray. Further experiments can be conducted to define the characteristics of materials based on their heating and cooling curves, for example, which would help improve the overall recovery rate.

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