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Recovering Critical Raw Materials from WEEE using Artificial Intelligence

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Abstract

In the last few years, Artificial Intelligence (AI) has assumed a key role in the Circular Economy (CE), and particularly in the waste management process by supporting fast and efficient sorting of materials with computer vision and object recognition. The system presented in this paper demonstrates that AI could be a valuable asset in waste of electrical and electronic equipment (WEEE) recycling. In fact, the obtained accuracy of classification equal to 80% corresponds to a significant improvement compared to current situation in the recovery of critical raw materials (CRM) from the WEEE in which the whole board is shredded and only a maximum of 10-15 chemical components are recycled, while the majority of the CRM are lost.

Keywords: Urban Mines, WEEE recycling, Circular Economy, Computer Vision, Machine Learning

1. Introduction

The recycling process underwent a profound transformation since it began in 1960, moving from consumer led sorting to downstream industrial facilities that could distinguish the different materials by their mechanical or spectral properties.

In recent years, many Artificial Intelligence applications have been developed to support Circular Economy in the recycling process. Nowdays, AI analyzes large quantities of data at high speed and can support CE throughout the entire value chain from demand prediction to re-manufacturing, unveiling aspects that are barely visible to humans (Berg et al., 2020; Akinode and Oloruntoba, 2020). In particular, AI can assist the waste management process by supporting intelligent sorting of materials with computer vision and object recognition, separating plastics, cardboard, cans, papers, etc. (Calaiaro, 2022) with significant improvements.

The European Green Deal (EGD) defined by the European Union Commission, is a roadmap to transform European Union into a modern and resource-efficient economy. In order to reduce the usage of new natural resources the new CE action plan (V.V.A.A., 2022a) in EGD aims at reusing valuable materials from waste throughout the whole product life-cycle. A circular production model also supports the creation of sustainable goods by relieving pressure on natural resources, in accordance with objective 12 of the United Nations document "Sustainable Development Goals" (V.V.A.A., 2022b) and fosters the transition to a sustainable, human-centric and resilient *Industry 5.0*.

Concerning the electronics market, recycled materials could then be employed in the production of new components or stocked in the so called *Urban Mines*, thus reducing the dependence on politically unstable markets, where *critical raw materials* (CRM) usually come from.

The list of 30 CRM (V.V.A.A., 2020) compiled by the European Commission encompasses those elements that require special attention due to their economic importance or supply risk, such as tantalum, beryllium, tungsten, gallium, etc.

CE turns into the enabling paradigm, extremely focused on CRM which are often irreplaceable in many products, that have become critical for EU growth and competitiveness (Magnus et al., 2018) by extending their lifespan and maintaining their economic value (Berg et al., 2020).

To implement a fully integrated CE model for the European electronic market, we should start at the very early stages of product design (Ghoreishi, Malahat and Happonen, Ari, 2020), setting up of a virtuous ecosystem, for efficiently recycling waste of electrical and electronic equipment (WEEE) aimed at pulling out and sorting homogeneus electronic compoments from the WEEE, in order to increase the yield of the extracted CRMs.

Pending a complete workflow that covers the whole EEE lifecycle also on the regulatory side, in this paper we present a project that tackles the recycling phase by proposing a real-time edge system capable of identifying the position of the Components Of Interest (COI) on an electronic board under a camera and eventually driving a *pick-and-place* robotic arm to selectively and efficiently dismount the desired items. Combining computer vision and machine learning, we can classify each component of an electronic board and sort it into a bin that contains homogeneous items only, noticeably boosting the yield in critical rare materials.

2. Materials and Methods

Our experimental setting encompasses two hardware platforms for model building and deploying respectively, due to the computational effort required at the relevant stages. In fact, the selected software solution is supported by YOLOv5 (Jocher et al., 2022), a *state-of-the-art*, real-time object detection system, based on convolutional neural networks (CNN) (Ankile et al., 2020), that is applied to the whole image to generate predictions that rely on the global context of the image.

A CNN is a type of artificial neural networks which is designed to learn spatial hierarchies of features that are highly efficient in image processing tasks. They are usually composed of convolutional and pooling layers, performing feature extraction, and fully connected layers for classification output (Yamashita et al., 2018).

In order to train our model to recognize the selected electronic components right on the board, we extended the pre-trained YOLO model by means of transfer learning (Weiss et al., 2016) to detect a set of 5 electronic components, leaving out surface mounted resistors and capacitors which look pretty much alike. The classes are

- resistor;
- capacitor (non electrolitic);
- electrolitic capacitor;
- coil;
- integrated circuit.

Last but not least, in order to efficiently deploy the building blocks of our system onto different hardware platforms, we run our solution inside a Docker container (Merkel, 2014), which provides a lightweight virtualization layer on the Linux operating system.

2.1. Model Building

This phase was executed on an Linux server platform, equipped with 2 Intel Xeon Silver 4214 CPU @ 2.20GHz, 93GB RAM and NVIDIA Quadro RTX5000 16GB with 3072 CUDA (Compute Unified Device Architecture) cores on the GPU (Graphics Processing Unit).

CUDA is a parallel computing platform by NVIDIA used by their GPU architectures to boost graphics operations and data processing. GPUs are responsible for creating images, scenes or rendering 3D graphics and can also be used to speed up machine learning applications.

Model Building can be divided into four subtasks, performed in the following order:

1. **Images preparation**: A number of electronic board images is collected and properly stored in specific folders; the images should contain instances of the desired classes with different rotations and lighting in order to achieve a good training. For the experiments described in this paper, we have been using 27 images (20 for training and 7 for validation) taken with a Jetson camera module from various boards.
2. **Images labeling**: This is the most crucial part of the training phase because it requires a lot of manpower to carefully locate the COIs and assign them the appropriate label. Each component may be rotated or partially visible and examples of all possible occurrences should be selected. The tool utilized in this task is a graphical image annotation tool named LabelImg (Tzutalin, 2015) written in Python (Van Rossum and Drake Jr, 1995) with Qt for its graphical interface. Annotations can be saved in various formats including the one used by YOLO.
3. **Model training**: The new classification model can be generated within the official YOLOv5 docker container and the provided Python scripts in less than 15 minutes for our data set. The newly generated model is immediately available for testing.
4. **Model export**: The new model is then deployed onto the target test platform, which will be detailed in the next section.

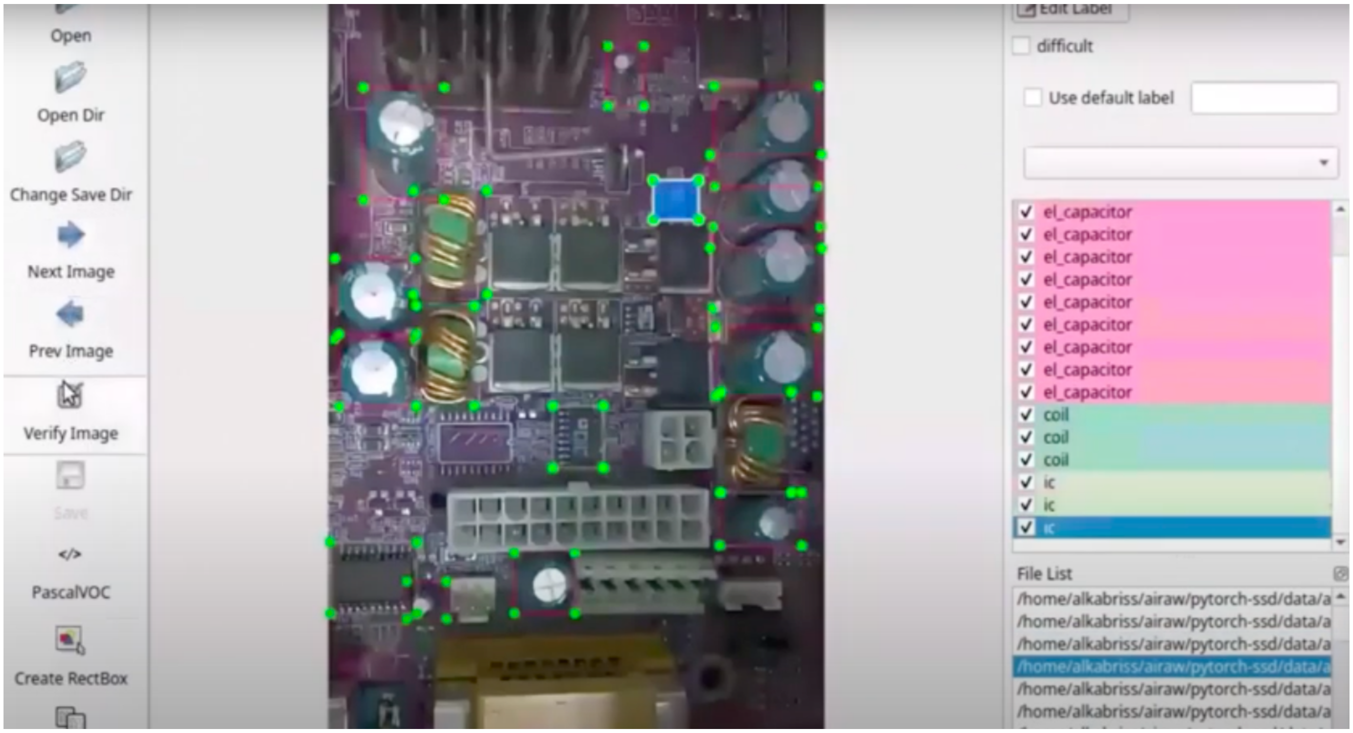

Figure 1. Screenshot of image labeling application running on the Linux server.

2.2. Model Deployment

Next, the built model is made available on the target platform, an NVIDIA Jetson Nano, with a Quad-core ARM® A57, 128-core NVIDIA GPU and 4GB RAM running a specialized Linux operating system for Tegra (JetPack 4.5).

Jetson Nano is a credit card size System-on-Module device providing remarkable results on edge AI applications, thanks to a tailored software development kit, included in JetPack, optimized for its best performance. This particular device was chosen to provide low cost parallel processing on the edge: our system should equip multiple AI-enhanced sorting conveyors therefore it is more efficient to process all video streams on the edge and instruct the robot with each object coordinates in the real world reference frame.

The new model can be loaded by a graphical application as of Figure 2 that interfaces a Camera Serial Interface (CSI) camera module for real-time video streaming. Furthermore, it is parallelized inside the GPU of the Jetson device whereas the video stream is dealt with by a multi-threaded OpenCV (Bradski, 2000) application written in Python.

To connect our system to a robotic actuator, we implement a mapping between picture coordinates, expressed in pixels, and the real world ones of the electronic waste, expressed in mm, by means of an homographic transformation defined in the calibration phase of the camera sensor (Chum et al., 2005).

A homography is a mapping between the coordinates of points on one plane to their equivalent points on another. It is defined as a 3x3 matrix **H** that transforms (x, y) in the camera view to (x', y') in the 3D world view, optionally scaling by a factor s as of Equation 1.

$$s \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

A minimum number of 4 points is required for OpenCV to compute the homography matrix but better correspondence is achieved with 7 to 10 points.

3. Results

The system described in this paper classifies all selected electronic components in real-time at the speed of 2 frames per second (fps) on the Jetson and over 30 fps on our server.

As shown in Figure 2, the application can successfully identify the vast majority of the components on the board, regardless of the poor lighting conditions of some image areas: this is visually represented on the video stream monitor where each distinct class of objects is associated to a different color.

The accuracy of classification obtained by the system presented in this article is about 80% (lower for the less represented classes in the data set, such as coils).

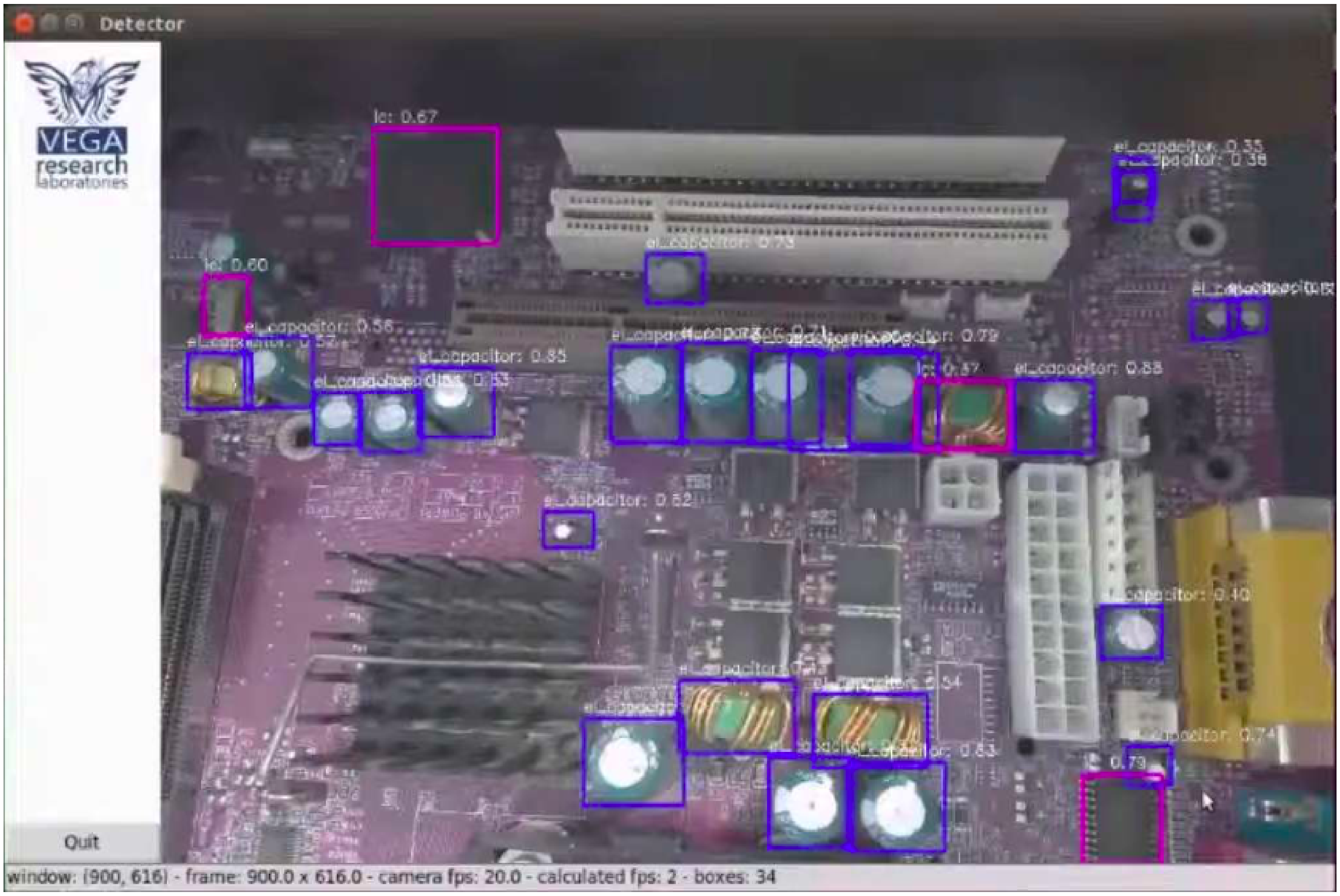

Figure 2. The real-time monitor application of the component detector. A sample video reel on image labeling and detection can be found at https://youtu.be/bWtwSNKnkWQ.

4. Discussion and Conclusions

Our project demonstrates that computer vision and AI applications on edge platforms could be a valuable asset in waste recycling and particularly for WEEE. In fact, the accuracy of classification obtained by the system presented in this article corresponds to a significant improvement compared to the current situation in the recovery of CRM from the WEEE in which the whole board is shredded and only a maximum of 10-15 chemical components, out of the approximately 50 elements present in the electronic boards, are recycled, while the majority of the CRM are lost.

Also note, the classification accuracy could easily be improved using a larger data set, for example including 500 images of electronic components, or more.

Moreover, an international regulatory framework that norms a sustainable EEE design process where each board comes with a detailed bill-of-materials, the position of each and every component on a board and a quantitative list of recoverable CRM could help establish a virtuous recycling process that minimizes the unrecoverable waste that is to be sent to landfill.

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References

Akinode, J. L. and Oloruntoba, A. (2020). Artificial intelligence in the transition to circular economy. *American Journal of Engineering Research*, 9:185–190.

Ankile, L. L., Heggland, M. F., and Krange, K. (2020). Deep Convolutional Neural Networks: A survey of the foundations, selected improvements, and some current applications. *arXiv:2011.12960*.

Berg, H., Blévennec, K. L., Kristoffersen, E., Strée, B., Witomski, A., Stein, N., Bastein, T., Ramesohl, S., and Vrancken, K. (2020). Digital circular economy as a cornerstone of a sustainable European industry transformation. White Paper - *ECERA European Circular Economy Research Alliance*.

Bradski, G. (2000). The OpenCV Library. *Dr. Dobb's Journal of Software Tools*, 120:122–125.

Calaiaro, J. (2022). AI Takes a Dumpster Dive: Computer-vision systems sort your recyclables at superhuman speed. *IEEE Spectrum*, 59(7):22–27.

Chum, O., Pajdla, T., and Sturm, P. (2005). The geometric error for homographies. *Computer Vision and Image Understanding*, 97(1):86–102.

Ghoreishi, Malahat and Happonen, Ari (2020). New promises ai brings into circular economy accelerated product design: a review on supporting literature. *E3S Web Conf.*, 158:06002.

Jocher, G. et al. (2022). ultralytics/yolov5: v6.1 - TensorRT, TensorFlow Edge TPU and OpenVINO Export and Inference.

Magnus, G. et al. (2018). *Report on critical raw materials and the circular economy*. European Commission, Directorate General for Internal Market, Industry, Entrepreneurship and SMEs.

Merkel, D. (2014). Docker: lightweight Linux containers for consistent development and deployment. *Linux journal*, 2014(239):2.

Tzutalin (2015). Labelimg. git code. https://github.com /tzutalin/labelImg.

Van Rossum, G. and Drake Jr, F. L. (1995). *Python reference manual*. Centrum voor Wiskunde en Informatica Amsterdam.

V.V.A.A. (2020). Critical raw materials resilience: Charting a path towards greater security and sustainability. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/ ?uri=CELEX:52020DC0474&from=EN [Accessed: 2022-04-11].

V.V.A.A. (2022a). Circular economy action plan. https://ec.europa.eu/environment/strategy/circular-economy-action-plan_it [Accessed: 2022-04-11].

V.V.A.A. (2022b). Sustainable development goals. *United Nations*, https://sdgs.un.org/goals [Accessed: 2022-04-11].

Weiss, K., Khoshgoftaar, T. M., and Wang, D. (2016). A survey of transfer learning. *Journal of Big Data*, 3(1):9.

Yamashita, R., Nishio, M., Do, R. K. G., and Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology. *Insights into Imaging*, 9(4):611–629.