



TREASURE

D6.1: Report on semi-automated disassembly

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EXECUTIVE SUMMARY

The TREASURE project aims to provide a chance for the automobile industry to become more circular. To achieve this goal, instruments that facilitate the creation of a circular supply chain are realized, allowing for the testing of various technologies. The Key Enabling Technologies (KETs), which were previously identified in the predecessor H2020 FENIX project, can be used into a variety of processes to yield tangible advantages, and enhance the effective recovery of secondary resources. The KETs in this deliverable include machine vision, AI, precision rework equipment, and cobotics (cobot). We will also see how these KETs can be integrated to support activities in the context of Industry 4.0 and how important they are to increasing the repeatability and efficiency of some complex operations, like PCBs (PCBs) disassembly.

The focus of D6.1 is to report on the developments of the semi-automatic PCBs disassembly system. Leveraging the results presented in D5.1 and D5.2, the document proposes a revised version of the pilot plant, addressing some of its key aspects to advance the development of an effective solution for tackling the issue of electronic component disassembly. Modifications were implemented on multiple fronts, and the use of AI in cobotics and AI-based vision systems has enhanced both the safety level for the operator and the process efficiency, further demonstrating the potential synergies among various KETs. Finally, the document will cover training sessions conducted in collaboration between POLIMI and POLLINI, where company operators experienced the proposed solution firsthand. The first section of the document discusses the insights gained during the TREASURE project on the theme of electronic component disassembly from PCBs boards. With this knowledge, it proposes the framework of the pilot plant solution, derived from the know-how acquired throughout the project and optimized from the previously proposed configuration. The second section provides an account of the tools and KETs chosen to support and enhance the process efficiency. It explains the context of the Industry 4.0 Laboratory where the pilot plant was developed, the state of the art in Human-Robot Collaboration (HRC), and the potential benefits of adopting a cobot solution. Finally, it details the selection of process tools, highlighting the various synergies between the different technologies employed. The third section develops the framework proposed in the first section by describing the technological development of the pilot plant. It delves into the implemented technologies; the cobot and the coupled vision system to ensure greater operator safety during the procedure, the new machine vision system capable of identifying integrated circuits on PCBs boards, and finally, the complete disassembly process defined as a pipeline of operations. The fourth section is dedicated to reporting on the training activity conducted in collaboration with the project partner POLLINI, where the pilot plant was tested in a laboratory setting to analyze its performance in an operational context. The sessions aimed to introduce operators to the concept of cobots and demonstrate how these solutions can assist them in a disassembly operation, offering them the opportunity to firsthand experience a collaborative solution. In the fifth and final section, the key considerations of the activities conducted within the scope of the disassembly pilot plant are summarized, outlining the path for future work, and deeply discussing the theme of potential technological barriers to the development of the optimal solution and the possible solutions emerged also during the TREASURE project.

TABLE OF CONTENTS

DISCLAIMER OF WARRANTIES	2
EXECUTIVE SUMMARY	3
1 Introduction.....	5
1.1. Scope of the deliverable	6
1.2. Contributions to other WPs.....	6
2 PCB disassembly methodology	6
2.1. State of the art in disassembly of electronic components	6
2.2. Analysis of previous solutions and trade-offs.....	7
3 The Industry 4.0 Laboratory and tools.....	9
3.1 The Industry 4.0 Laboratory	9
3.2 State of the art in Human Robotic Collaboration	10
3.3 Equipment and Tools	11
3.3.1 The UR5e.....	11
3.3.2 The custom air-desolderer	11
3.3.3 The pre-heating plate	11
3.3.4 The Intel D435i camera.....	12
3.3.5 The workstation for AI training	12
4 Pilot plant configuration.....	13
4.1 Configuration of the pilot plant	13
4.2 Component detection related features	14
4.2.1 Enhancement of computer vision algorithm capabilities	14
4.2.2 AI implementation for Integrated Circuits detection.....	16
4.3 Safety related features	19
4.3.1 Working area limitations.....	20
4.3.2 Hand detection capabilities.....	20
4.3.3 Remarks on the safety solutions implemented	21
4.4 Pipeline of the semiautomated disassembly process.....	22
4.4.1 SMD components disassembly	22
4.4.2 TH components disassembly.....	24
5 Training of POLLINI operators	25
5.1 Scope of the training.....	25
5.2 Training sessions	25
5.1.1 Preliminary session.....	26
5.1.2 Session one.....	27
5.1.3 Session two.....	28

5.3 Results and feedback.....	30
6 Future work and Conclusions.....	30
6.1 Technological barriers and mitigation actions	30
6.2 Profitability analysis.....	31
6.3 Conclusions and future work.....	32
7 References.....	32
8 Abbreviations	33

List of figures

Figure 1	The computer vision algorithm developed in the prior plant configuration
Figure 2	The cobots in the Industry 4.0 Laboratory at the Politecnico di Milano
Figure 3	The CV Lab4.0
Figure 4	The custom holder for the air-desolderer
Figure 5	The preheating plate and the modified frame
Figure 6	The Intel Depth Camera D435i
Figure 7	Schematics of the new solutions adopted
Figure 8	Results of the background removal algorithm
Figure 9	Results of the edge detection algorithm
Figure 10	Results of the detection algorithm after patch extraction
Figure 11	Structure of the pipeline for components classifications
Figure 12	Visual output of a segmentation network
Figure 13	Results of the transfer learning
Figure 14	Bounding boxes in red drawn by the AI algorithm on the combi-instrument PCBs
Figure 15	Two of the four planes defined to limit the cobot workspace
Figure 16	Tracking of operator’s hand during disassembly operation
Figure 17	Semi-automated procedure of removal of SMD
Figure 18	Removal of TH components
Figure 19	Structure of the training sessions
Figure 20	Pollini’s manager interacting with the cobot in the Industry 4.0 Laboratory at the Politecnico di Milano
Figure 21	Pollini’s operator performing a manual tool change operation equipping the robot with a two-finger electric gripper
Figure 22	Pollini’s operator during the explanation of the computer vision solutions
Figure 23	Pollini’s operator testing the cobot and the pilot plant for semi-automated PCB disassembly

List of Table

Table 1	Energy consumption for disassembly of Ibiza IV series
Table 2	Energy consumption for disassembly of Leon II series
Table 3	Energy consumption for disassembly of Ibiza V series

1 Introduction

1.1. Scope of the deliverable

The objective of Deliverable 6.1 is to articulate the progress made in the development of the semi-automated printed circuit board (PCB) disassembly system. Building upon the findings delineated in Deliverables 5.1 and 5.2, this document introduces an updated version of the pilot plant, targeting crucial modifications to propel the evolution of a viable solution for the disassembly of electronic components. Enhancements have been realized across various dimensions, with the integration of AI in cobotics and AI-enhanced vision systems significantly elevating both the safety standards for operators and the overall efficiency of the process. This advancement underscores the collaborative potential of Key Enabling Technologies (KETs). Furthermore, the deliverable will detail the training sessions executed in partnership between Politecnico di Milano (POLIMI) and Autodemolizione Pollini (POLLINI), wherein company operators engaged directly with the refined solution, offering practical insights into its application.

1.2. Contributions to other WPs

This deliverable builds on the foundation laid in the deliverable D5.2, "Pilot-scale reconfiguration, testing and optimization of a semi-automated PCB disassembly process" by implementing its defined framework and optimizing disassembly procedures, increasing efficiency and safety. The pilot will be, then, integrated in the TREASURE Digital Toolbox according to the architecture outlined in D4.1 giving in output the metrics of energy consumption related to the disassembly operations. The insights for recycling performance are largely drawn from D3.3, "Recyclability Analysis," utilizing the gathered data to steer the evolution of disassembly processes.

2 PCB disassembly methodology

2.1. State of the art in disassembly of electronic components

Considering the burgeoning global recognition of Waste from Electrical and Electronic Equipment (WEEE) as an invaluable secondary source for CRMs and rare earth elements, there persists a notable discrepancy between the theoretical potential and the empirical recovery rates. This divergence stems primarily from the prevailing industrial-scale recycling technologies' predisposition towards extracting materials manifesting in higher concentrations, attributable to the conspicuously low efficiency of current recycling processes in salvaging elements found in less abundant concentrations. Such a phenomenon is elaborately documented, elucidating the inefficiencies in recuperating materials that are sparsely distributed, primarily due to their minimal concentrations relative to the overall mass. This bias towards more abundantly present materials results from the conspicuously low efficiency of present-day recycling processes in salvaging elements found in lesser concentrations, a limitation thoroughly documented in D3.3. This document elucidates that the inefficacy in recuperating these sparsely distributed materials stem from the fact that certain valuable elements, though existent on electronic boards, manifest in minimal concentrations compared to the overall mass. Consequently, there is a pronounced emphasis on the recovery of materials that are more readily available in substantial quantities, highlighting an urgent need for innovative methodologies that could substantially enhance the recovery of materials traditionally marginalized by conventional recycling approaches.

The evolution towards more refined disassembly and recycling methodologies encounters numerous critical challenges, encompassing both technical and economic dimensions,

particularly concerning the minimal concentration of rare materials on electronic boards. Addressing these challenges necessitates the processing of extensive quantities of material to sufficiently supply optimized recycling processes. Innovations in the domain, as epitomized by the pioneering electronics disassembly plant delineated by Zebedin, H., Daichendt, K., & Kopacek, P. (2001), along with subsequent methodologies introduced by Park, S., Kim, S., Han, Y., & Park, J. (2015), signify the progressive advancements in disassembly technologies. Nevertheless, these methodologies also underscore enduring limitations in navigating the crucial component selection phase, which is imperative for optimizing recycling processes.

The advent of Industry 4.0 technologies, encompassing AI, machine vision, and cobotics, proffers promising pathways to surmount these obstacles. The proliferation of intelligent systems, adept at managing the uncertainty and intricacy associated with WEEE through sophisticated learning and revision processes, heralds a pivotal transformation towards more efficacious and environmentally sustainable recycling practices. The deployment of cognitive robotics, furnished with intelligent systems for autonomous decision-making, epitomizes a significant leap forward in addressing the quandaries presented by the high complexity and heterogeneity of EoL products.

Moreover, the conceptualization of an intelligent disassembly system, proffers a visionary blueprint for the integration of cutting-edge technologies to foster flexibility, efficiency, and adaptability in the recycling of WEEE. This paradigm not only endeavours to ameliorate the recovery of precious materials but also aligns with the broader imperatives of the CE by minimizing environmental ramifications and conserving finite resources. In essence, Yingqi Lu, Weidi Pei, Kaiyuan Peng (2023) accentuate the imperative for groundbreaking disassembly and recycling technologies capable of adeptly circumnavigating the complexities inherent in WEEE.

The infusion of Industry 4.0 technologies harbours significant potential to revolutionize recycling practices, charting the course towards a more sustainable and efficient paradigm of resource recovery and environmental stewardship. The D5.2 aimed to delve deeper into this discussion, offering a preliminary exploration of the innovative technologies that hold potential for application in this domain, thereby paving the way for a more efficient and sustainable approach to PCB recycling. This deliverable instead, will examine the potential enhancements implemented to the previous solution proposed during the final months of the project's duration.

2.2. Analysis of previous solutions and trade-offs

The second configuration of the pilot plant for the semi-automated disassembly of printed circuit boards (PCBs) presented in the deliverable 5.2 of the TREASURE project underlines an optimized approach that aims to address the complexities and limitations encountered in the initial configuration. This reconfiguration, driven by the need to enhance efficiency, safety, and cost-effectiveness, embodies the integration of advanced technologies such as cobotics and computer vision. The core objective of this revamp is to refine the disassembly process for extracting CRMs from automotive electronic components at EoL, thereby supporting the CE within the automotive sector.

The process begins with the preparation phase, where the operator places the PCBs on a preheating plate equipped within the pilot plant setup. This preheating phase is crucial for softening the soldering material, thus facilitating the subsequent removal of components from the PCB. Once the PCB reaches the requisite temperature, the disassembly process initiates with the operator manually removing through-hole (TH) components. This manual intervention is

necessary due to the variability in sizes, shapes, and attachment methods of TH components, which may require end-effectors capable of managing those criticalities.

The process then transitions to the removal of SMDs components. This stage utilizes a hand-eye system, comprising a cobot equipped with an air desoldering device and guided by advanced computer vision algorithms. The algorithms are designed to identify SMD components on the heated PCB, enabling the cobot to accurately and efficiently desolder and remove the targeted components with minimal operator assistance.

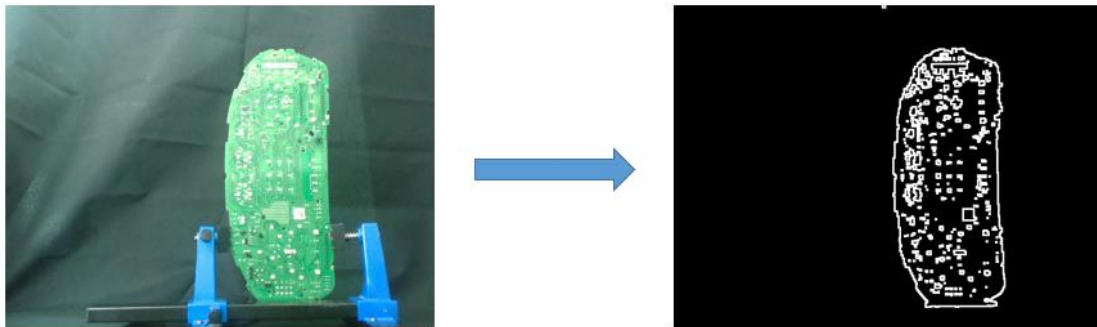


Figure 1. The computer vision algorithm developed in the prior plant configuration.

One of the enhancements in this configuration is the application of computer vision algorithms designed to detect specific components on the PCBs. This capability is critical for identifying SMD components, which, due to their diminutive size and intricate soldering, pose substantial challenges in the disassembly process. Although innovative, this solution lacks the capability to discern the various types of SMDs present on the PCBs, consequently directing the robotic system towards a comprehensive disassembly of SMD components, which undermines the overall efficiency of the solution. As has been elucidated over the course of the project, a complete disassembly of PCBs is not requisite; rather, a disassembly targeted towards components that contain CRMs in higher concentrations is paramount. The utilization of AI-powered image recognition, described in this deliverable, allows for selective disassembly, whereby the system focuses on components containing valuable CRMs, thus averting the need for complete disassembly.

The trade-offs in this reconfiguration underscore the imperative for heightened safety measures and the development of sophisticated computer vision algorithms. The proximity of human operators to the cobots necessitates rigorous safety protocols to prevent accidents, especially during the handling of heated tools. Moreover, the effectiveness of the computer vision system is contingent upon its ability to accurately identify and classify the various components on a PCB, which requires continuous refinement of the AI models to adapt to the diversity of PCB designs and the evolution of electronic components.

The emphasis of the proposed solution delineated in this document is centered on refining the procedure for the removal of SMD components by augmenting the plant's capabilities beyond the sole reliance on computer vision technologies. The limitations inherent to computer vision-based approaches will be discussed in the subsequent section. Instead, the plant will incorporate algorithms rooted in AI, which possess the proficiency to discern the specified components and accurately direct the cobot towards their precise locations. The adoption of these new solutions effectively enables selective disassembly, equipping the algorithms with the capability to distinguish between desired electronic components, thereby significantly enhancing the

automation of the entire process and facilitating completely automated desoldering. Additionally, the ability to select only the desired components substantially reduces the processing time of the electronic board by avoiding unnecessary desoldering of irrelevant components. Furthermore, pioneering solutions, once more predicated on AI, have been investigated with the objective of diminishing the risks entailed by the operator's proximity to a cobot tool deemed hazardous.

3 The Industry 4.0 Laboratory and tools

3.1 The Industry 4.0 Laboratory

This segment delineates the Industry 4.0 Laboratory (I4.0 Lab) managed by the Manufacturing Group within the Department of Management, Economics, and Industrial Engineering at the Politecnico di Milano (www.polimi.it). As elucidated by Fumagalli et al. (2013), the I4.0 Lab constitutes a concrete, physical domain designed for conducting research within a simulated Industry 4.0. It stands as a fundamental node for the propagation of Industry 4.0 comprehension and awareness across both industrial and academic spheres. The laboratory encompasses an assortment of systems to facilitate various research undertakings: it features a comprehensive production line, incorporating technologies at the forefront of Industry 4.0; an Automated Guided Vehicle (AGV) dedicated to the oversight of logistical information systems; and a Franka Emika Panda Cobot, a Universal Robot UR5e depicted in figure N, and several workstations used for robotic programming and AI solutions training.



Figure 2. The cobots in the Industry 4.0 Laboratory at the Politecnico di Milano

The laboratory is currently undergoing an extensive refurbishment, with the aim of integrating additional technologies pertinent to Industry 4.0. This endeavour is intended to bolster research initiatives within this domain and to furnish students and researchers with advanced tools. Such an initiative will enable them to directly engage with and experiment with innovative methodologies, thereby enriching their practical understanding and application of Industry 4.0 concepts. Furthermore, a novel segment has been recently incorporated into the laboratory, instigated by the requisites delineated by the TREASURE project. This led to the creation of a space expressly constructed to facilitate superior image capture alongside the requisite infrastructure for processing these images, with its inaugural setup illustrated in Figure 3.

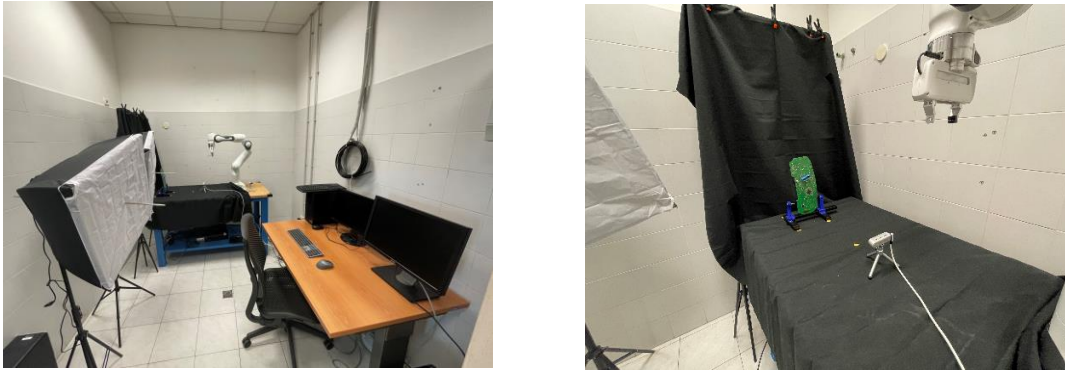


Figure 3. The room in the I4.0Lab dedicated to computer vision

3.2 State of the art in Human Robotic Collaboration

In accordance with the ISO/TS 15066:2016 standard ("ISO/TS 15066:2016 - Robots and robotic devices—Cobots." 2016. [Online]. Available: <https://www.iso.org/standard/62996.html>), a cobot (cobot) is characterized as a robot capable of executing tasks in conjunction with humans within a designated workspace, specifically designed for mutual operation. The safety protocols and performance criteria for cobots are further delineated by the ISO 10218 safety standard ("ISO 10218-1:2011 - Robots and robotic devices — Safety requirements for industrial robots — Part 1: Robots." 2011. [Online]. Available: <https://cutt.ly/BNuekXF>) and the RIA ISO/TS 15066 technical specification, which outline four distinct Cobot Operations:

- Safety-rated monitored stop, enabling a robot to pause its motion when a human enters the collaborative workspace;
- Hand-guiding operation, permitting an individual to guide the cobot to a specific location without prior training;
- Speed & separation monitoring, ensuring the cobot maintains a certain velocity as long as a specified distance from the human is preserved;
- Power and force limiting, designed to detect and limit unintended or intended physical contact between the robot system (including the workpiece) and the human operator, to uphold the utmost safety standards.

These operational modes afford novel opportunities for human-robot cooperation yet introduce certain constraints to the systems' operational capabilities. Human-Robot Collaboration (HRC) is identified as a pivotal research domain with the potential to significantly advance CE by fostering the development of remanufacturing and recycling frameworks within the Industry 4.0 paradigm (Rocca et al., 2020; Daneshmand et al., 2022). The synergy of human and robotic efforts facilitates the reassignment and distribution of tasks, with robots undertaking hazardous activities and humans directing the robots towards higher-value tasks, enhancing job satisfaction (Alvarez-delos-Mozos et al., 2020). Despite the challenges in implementing many HRC features in industrial settings, their development is deemed crucial for innovating processes aimed at reducing (Alvarez-delos-Mozos et al., 2020). The versatility afforded by cobots, capable of operating near humans without barriers, enables the design of flexible procedures adaptable to varying disassembly requirements (Kerin & Pham, 2019). In the context of the project, the cobot plays a pivotal role in facilitating the automation of disassembly processes for various types of PCBs (Cesta et al., 2016). Although the diversity of PCBs subject to disassembly is substantial, human guidance remains essential, especially in the initial stages of process development, to adapt the cobot to new tasks. It remains a subject of discussion whether human intervention will continue to be necessary upon the completion of this application's

development. The aim is to evolve towards a flexible solution where human involvement is minimized, potentially confined to overseeing multiple PCB disassembly systems simultaneously. Given the narrow profit margins associated with such applications, the cost implications of human labour significantly influence the financial viability of the system.

3.3 Equipment and Tools

3.3.1 *The UR5e*

In the development of the pilot plant, the Universal Robot UR5e, with its 5kg payload capacity, was deemed the most apt instrument for assisting the operator in the disassembly of PCBs, not only due to its payload but also in terms of its dimensions. This cobot (cobot) is equipped with an online programming interface facilitated by Polyscope software, which enables the programming of the cobot's actions through straightforward instructions. While offline programming offers a user-friendly approach to cobot programming, for the objectives of this pilot plant development, it was decided to employ the Robot Operating System (ROS) as the interface. ROS is a middleware platform that enhances the interaction between robotic systems and external sensors, thereby streamlining the programming process of the cobot in the context of developing applications of this nature.

3.3.2 *The custom air-desolderer*

To accommodate the operational requirements of the pilot plant, a bespoke tool holder was conceptualized to facilitate the attachment of the selected desoldering tool to the wrist of the cobot (cobot). To realize this, a specialized holder was engineered and subsequently manufactured through the process of additive manufacturing.



Figure 4 – The custom holder for the air-desolderer

3.3.3 *The pre-heating plate*

For the disassembly process, an air-desoldering unit, commonly utilized in PCB rework applications, and a JBC preheating plate, adequately sized to accommodate a diverse range of board dimensions, were selected. The latter was chosen for its versatile temperature control capabilities, including the ability to set specific temperature profiles and to utilize control and reference thermocouples. The preheating plate facilitates a maximum temperature increase of 2°C per second, ensuring a gradual heating process of the PCB that prevents any potential damage or thermal shock. The plate can achieve temperatures up to 250°C, which, when appropriately applied, enables the desoldering of components from the board. This operational temperature range is conducive to a safe heat treatment process that accommodates the presence of an operator while mitigating the risk of damage to the PCBs. The control of the preheating process can be managed either through the provided control interface or remotely via Ethernet connection to a workstation or robot, offering a precise and adaptable solution for

this specific application. The preheating plate is also equipped with a modular frame designed to secure a broad spectrum of PCBs. We have made modifications to this frame to facilitate easier interaction between the cobot and the operator, by reinforcing certain areas and adding supports to prevent the PCBs from dislodging from the holder under the application of external forces.



Figure 5 – The preheating plate and the modified frame

3.3.4 The Intel D435i camera

A hand-eye coordination system, which leverages data from computer vision technologies alongside the adaptability and accuracy of robotic mechanisms, significantly enhances the capabilities of a cobot, particularly within the domain of Printed Circuit Board (PCB) disassembly. Consequently, we have incorporated an Intel Depth Camera D435i with the cobot. This specific camera model is equipped with an integrated Inertial Measurement Unit (IMU) that can autonomously process depth information from images, in addition to capturing an RGB (Red, Green, Blue) image. The selection of this sensor is attributed to its compact form factor and the versatility afforded by the integration of a stereo vision system with RGB capabilities. In preceding iterations of the system, this camera was utilized to supply imagery for the computer vision algorithms. In the revised configuration, as detailed in Section X, it will facilitate the introduction of novel functionalities. This adaptation is necessitated by the requirements of AI algorithms, which demand cameras with a higher dots per inch (dpi) specification.



Figure 6 – The Intel Depth Camera D435i

3.3.5 The workstation for AI training

A workstation designated for AI training necessitates specific hardware and software characteristics to efficiently handle the computationally intensive tasks associated with machine learning and deep learning processes. Primarily, such a PC must be equipped with a high-performance Graphics Processing Unit (GPU) with substantial memory capacity, as GPUs accelerate the mathematical computations fundamental to AI training. Additionally, a robust Central Processing Unit (CPU) with multiple cores is essential to efficiently manage the overall system operations and parallel processing tasks. A significant amount of Random-Access Memory (RAM) is required to support the large datasets typically involved in AI training,

ensuring smooth data processing, and minimizing bottlenecks. Fast, ample storage, preferably Solid-State Drives (SSDs), is crucial for quick data retrieval and storage of extensive datasets and model checkpoints. For this reason, to meet the needs related to the training of the model used in the pilot plant, it was chosen to use an ad hoc configured Dell Workstation that reports the following characteristics:

- Nvidia RTX A4000, 16 GB VRAM
- 32 GB, 4 x 8 GB, DDR4
- Intel Xeon Silver 4208 (11 MB cache, 8 cores, 16 threads, 2.10 GHz to 3.20 GHz Turbo, 85 W)
- 1TB SSD

The configuration described facilitated the execution of model training within a matter of hours and achieved a substantial, albeit not yet optimal, near real-time inference rate for the model.

4 Pilot plant configuration

4.1 Configuration of the pilot plant

The final configuration of the pilot plant aimed to integrate the expertise acquired throughout the project concerning the disassembly of electronic components from PCBs. Leveraging this accumulated knowledge, innovative technological solutions were adopted to enhance both the effectiveness and safety of the proposed system.

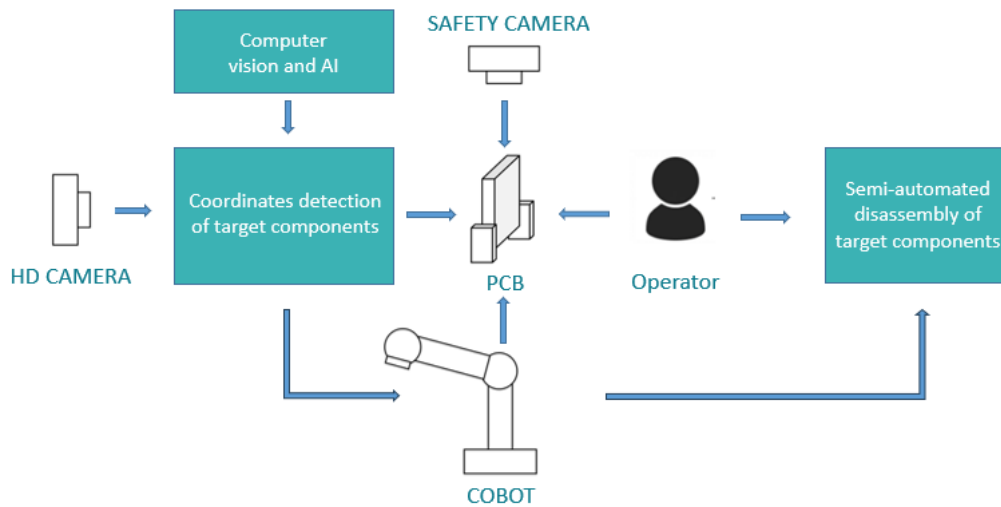


Figure 7. Schematics of the new solutions adopted

In terms of effectiveness, efforts were directed towards augmenting the cognitive capabilities of the system. This was achieved by evaluating the constraints associated with traditional computer vision techniques and exploring the potential advantages and limitations of AI-based solutions. Particularly, AI was examined for its capacity to reconstruct information in the EoL phase of automotive electronics, a challenging task due to the quantity and quality of data available. Regarding safety, initiatives were undertaken to mitigate potential risks faced by operators during disassembly processes. Although cobot systems are designed as collaborative tools and are certified as safe by manufacturers, they can lose this characteristic when equipped with potentially hazardous end-effectors, such as pointed, sharp, or heated tools. To address these issues, novel Human-Robot Collaboration (HRC) strategies were explored and implemented. These strategies are predicated on the ability to monitor the operator's

movements in relation to the cobot’s end-effector, enhancing safety. Furthermore, the cobot’s operational area was restricted exclusively to the designated disassembly zone, thereby bolstering the fundamental safety functions, and minimizing the workspace to enhance operator safety during interactions.

4.2 Component detection related features

As foreshadowed in the preceding section, this segment will delve into the progression of computer vision technologies designed for the identification of electronic components, developed within the framework of the pilot plant. Specifically, we will explore the advancements and evolutions of the solution introduced in the most recent pilot plant configuration, alongside a newly developed computer vision approach based on AI aimed at recognizing integrated circuits (ICs) on PCBs. Additionally, this analysis will address the primary challenges encountered during these developments and discuss the requisite performance levels necessary for achieving an optimal solution.

4.2.1 Enhancement of computer vision algorithm capabilities

The initial emphasis of the research in the domain of electronic component identification was centered on enhancing the performance of the first computer vision-based solution. The implemented solution in the earlier configuration, while capable of detecting the presence or absence of a generic SMDs component, failed to distinguish and categorize the class of the components. This limitation significantly impeded the efficiency of the disassembly process, necessitating the removal of all identified components on the board. As previously indicated, the complete disassembly of the PCBs does not yield substantial benefits; rather, disassembly efforts should be selectively concentrated on specific components. In essence, the methodology employed retains a resemblance to the previous approach, specifically, the construction of a pipeline consisting of sequential computer vision algorithms. This cascade of algorithms is utilized to systematically extract the requisite information from the images. Initial attempts were made to improve image segmentation performance. This involved the development of a preliminary background removal algorithm aimed at eliminating all elements from the image other than the electronic components.

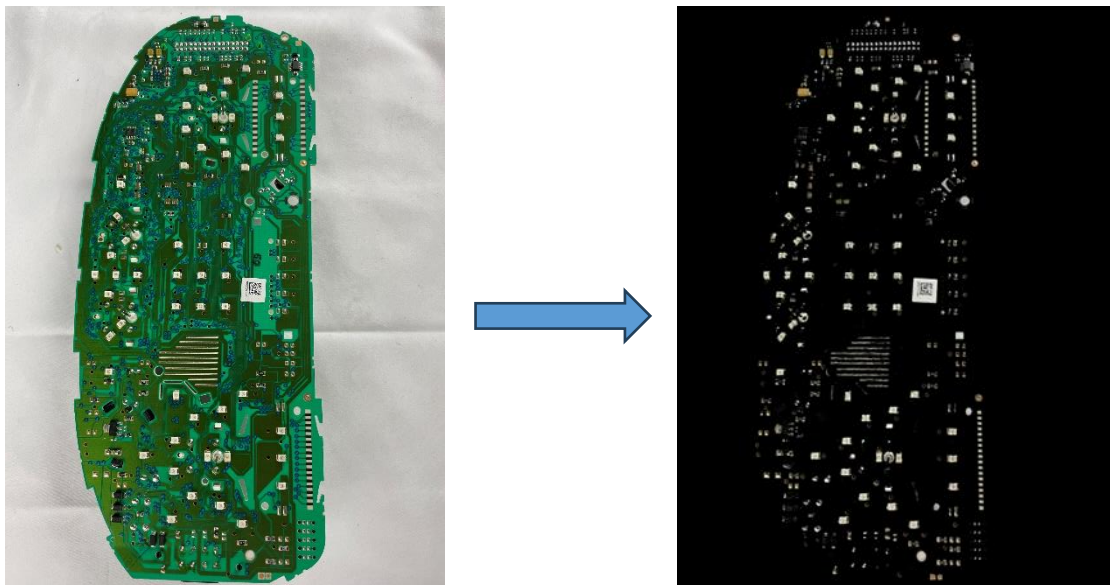


Figure 8. Results of the background removal algorithm

This algorithm focused on removing background colours, primarily the surface of the board itself, to enhance the clarity and focus on the components. Once the electronic components were isolated by the background removal algorithm, a subsequent edge detection algorithm was deployed to delineate bounding boxes around the identified components. The objective of this second algorithm was to establish coordinates for each component, enabling the extraction of individual patches. These isolated patches were then inputted into another algorithm designed for the classification of the components. This step was critical in facilitating the precise identification and categorization of components within the system. In Figure 9 we can see the outcome of the edge detection algorithm; the bounding boxes, delineated in green by the algorithm, are visible at the identified edges.

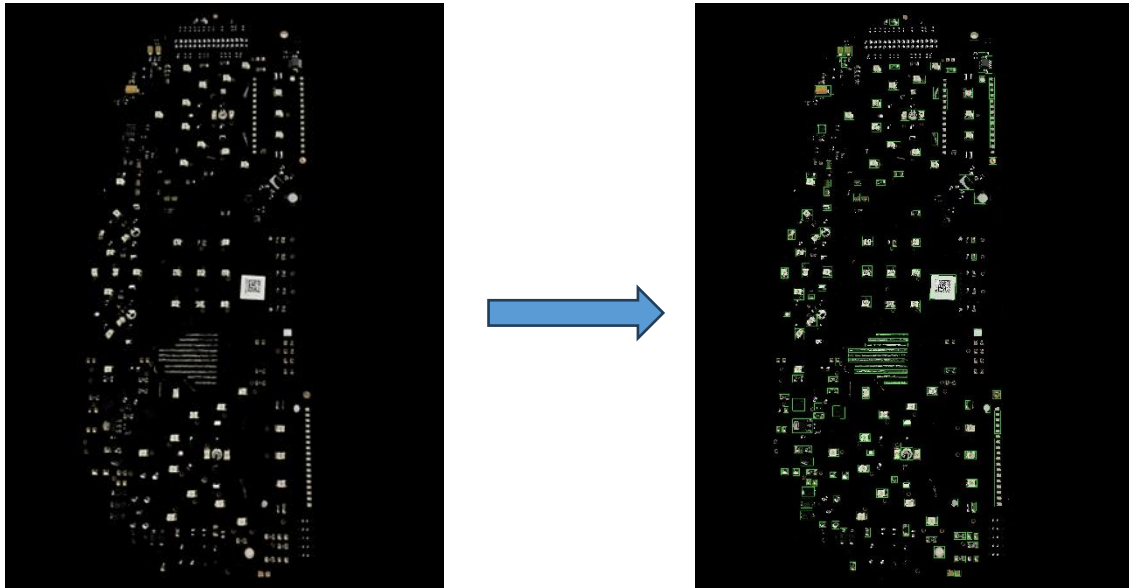


Figure 9. Results of the edge detection algorithm

As evident from the displayed figure, the algorithm isolates individual components on the board by encircling the relevant segment of the image with a bounding box. Once isolated, these components are cropped from the image and saved as patches, which are subsequently inputted into classification algorithms. The classification algorithm is designed to identify specific features within patches, such as colour or size, that can uniquely distinguish the extracted component. In this instance, an algorithm was created to detect tantalum capacitors based on their established value and distinctive colour association. Although the algorithm generally performs effectively, it is observable that some of the patches do not represent actual components but rather other elements of the PCBs not pertinent to electronic components. This issue arises because the features used to define a component, regardless of their engineering precision, do not consistently ensure the reliability of the intended target search.

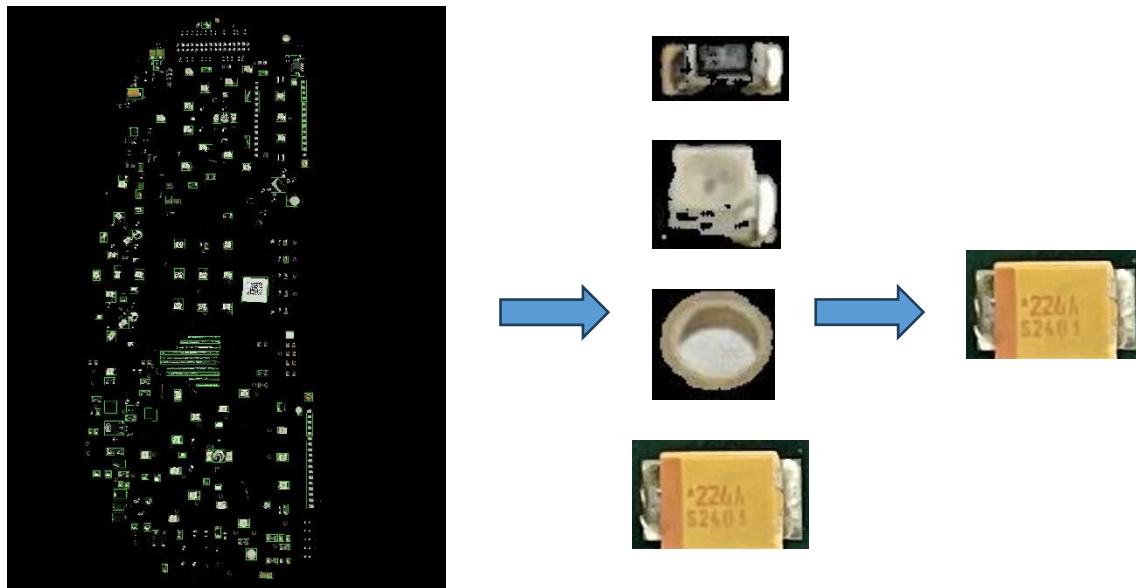


Figure 10. Results of the detection algorithm after patch extraction

The algorithmic pipeline, initiating with the board image, undergoes a sequence of transformations aimed at isolating the desired component. The most challenging aspect of this procedure is the final identification phase, where, regrettably, the incidence of false positives significantly undermines the robustness of the solution. The outcomes from the development of this pipeline have demonstrated that traditional computer vision techniques alone are inadequate for achieving robust solutions in the challenging task of PCBs component identification. Consequently, more sophisticated approaches that offer greater capability for context abstraction are required. Therefore, in the subsequent section, we will explore the development of this work using AI-based algorithms, which have been observed to exhibit substantially enhanced performance during experimental studies.

4.2.2 AI implementation for Integrated Circuits detection

In response to the limitations encountered in the development of a computer vision-based solution for the identification of PCBs components, it was determined that exploring AI-based solutions would be advantageous. These solutions, due to their inherent capacity for greater abstraction compared to conventional algorithms, enable the creation of more robust systems capable of systematically extracting information from PCB images. The primary objective remains the identification and localization of PCB components, with the aim of determining the coordinates and class to which each component belongs. Consequently, the initial step involved theorizing an optimal solution adept at performing these tasks. The sequence of AI models required to extract the desired information is illustrated in the accompanying figure:

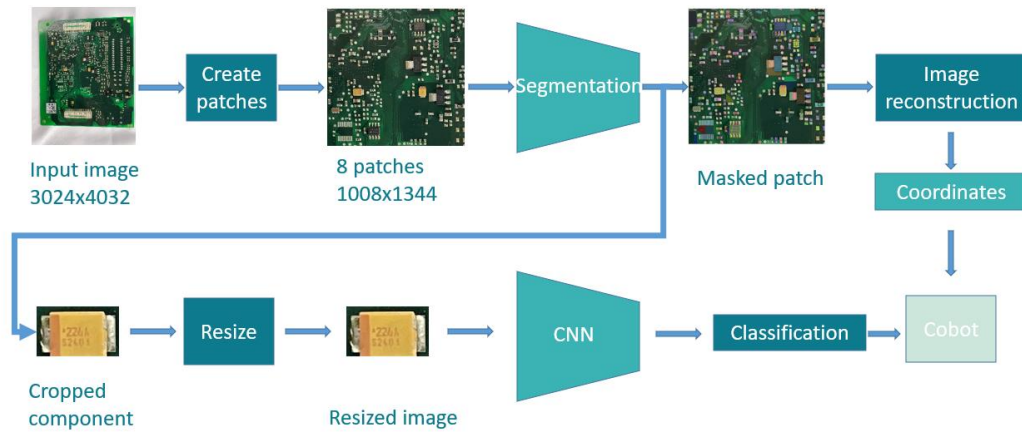


Figure 11. Structure of the pipeline for components classifications

The methodology depicted in the figure separates the localization and classification processes. The first network, illustrated at the top of the image, is designated for image segmentation. A segmentation neural network is a type of deep learning model designed to perform image segmentation tasks, which involve dividing a digital image into multiple segments (sets of pixels). The primary goal of such networks is to label each pixel in the image with a class corresponding to what the pixel represents. These models typically use a convolutional neural network (CNN) architecture, which processes the image through multiple layers of filters, extracting features at various scales and complexities. The network then applies these features to predict the class of each pixel individually, effectively segmenting the image. Segmentation neural networks are trained using a set of images with known segmentations (ground truth), and they learn to minimize the difference between their predicted segmentations and the ground truth during training.

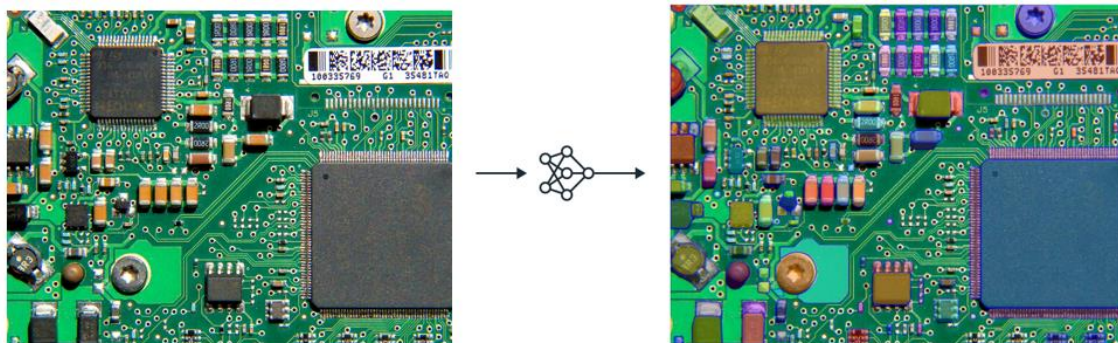


Figure 12 – Visual output of a segmentation network

Once the image has been segmented and the individual component images extracted, the task then shifts to identifying these components. This requires a model that, when adequately trained, can determine the class of the extracted components; the architecture of the network in this scenario must be specifically designed to address the complex challenge of classifying PCB components effectively. While the architecture of the solution described constitutes a viable and effective approach for implementing a pipeline of algorithms designed to identify and classify PCB components thus allowing the recovery of CRMs, procuring enough data for training neural networks for classification task proved challenging. This predicament, which will be extensively detailed in Section 6.1, necessitated a deviation in the development process towards a technically distinct, yet comparably effective, methodology. Following an exhaustive literature

search regarding known models and datasets for this type of application the WPCB-EFA dataset (C. Pramerdorfer and M. Kampel 2015) was identified as a candidate dataset; this dataset contains data on ICs in image and coordinates format; despite chemical composition of ICs varies based on the specific type of integrated circuit taken into exam, notably, they contain valuable and critical metals, albeit in minor amounts. Furthermore, these components have been found in substantial quantities in terms of mass of electronic components on the examined PCBs. "The dataset contains 748 images of PCBs from a recycling facility, captured under representative conditions using a professional DSLR camera. For all these images we provide accurate segmentation information for the depicted PCBs as well as bounding box information for all Integrated Circuit (IC) chips (9313 samples)." (C. Pramerdorfer and M. Kampel 2015). The focus then has been on finding an algorithm capable of being trained on the dataset identified. It was chosen to use a procedure similar to that illustrated by (Silva, Leandro & Júnior, Agostinho & Azevedo, George & Oliveira, Sérgio & Fernandes, Bruno. 2021). The idea is to perform transfer learning starting from the open source YOLOv5 model and adapt its object detection capabilities through a refined training on the WPCB EFA dataset, allowing recognition of ICs present on the PCBs. YOLOv5 is a popular real-time object detection system known for its speed and accuracy, which processes images in a single evaluation pass, predicting bounding boxes and class probabilities directly from full images. Transfer learning involves adapting a pre-trained YOLOv5 network to a new, but related task, leveraging the learned features from the original training to achieve high performance with relatively little additional training data. The YOLOv5 model, originally trained on a large and diverse dataset, is used as a starting point; the pre-trained network already can recognize a wide range of features, which are generally applicable across different visual recognition tasks. When adapting to a new task, like in the case of electronics component detection, the general approach involves freezing the early layers of the network that capture universal features (like edges and textures), while retraining the deeper layers that capture more specific features relevant to the new task. The application of this methodology proves particularly efficacious in scenarios where there is an insufficient amount of data to achieve adequate performance through training models from scratch.

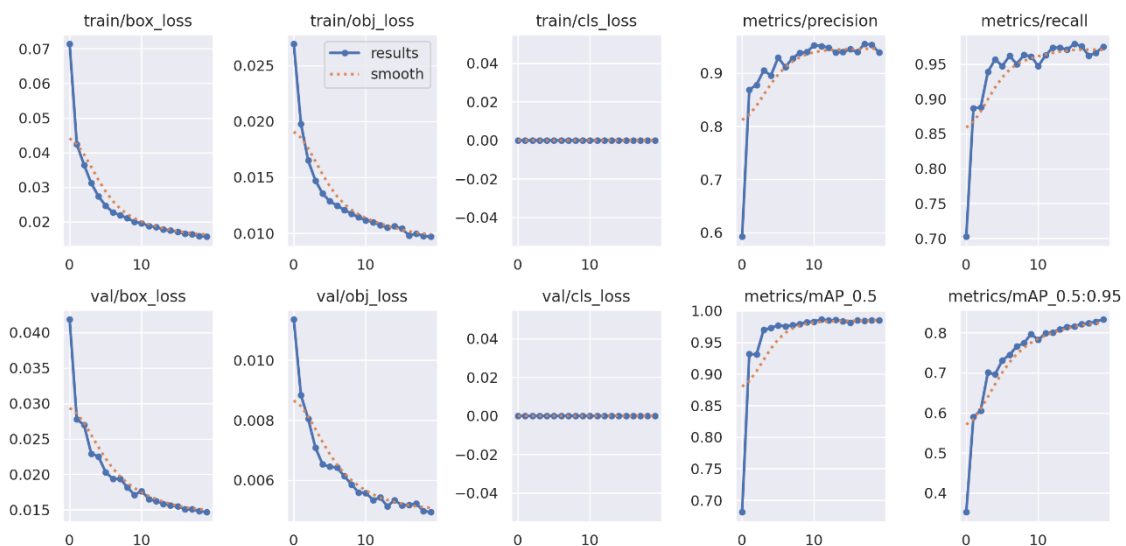


Figure 13. Results of the transfer learning

As evidenced by figure 13 depicting the results of transfer learning, despite the limited data available, the model ensures adequate performance for the identification task. Upon completion

of the training, the model was further evaluated through real-world case studies involving various types of PCBs, extending beyond those specifically considered during the TREASURE project. This was conducted to assess the model's performance and its capacity for abstraction in diverse practical scenarios. Despite the initial validation of the model's effectiveness during preliminary testing, it became apparent that while the model was adept at identifying large ICs, it struggled with the detection of the smaller ones.

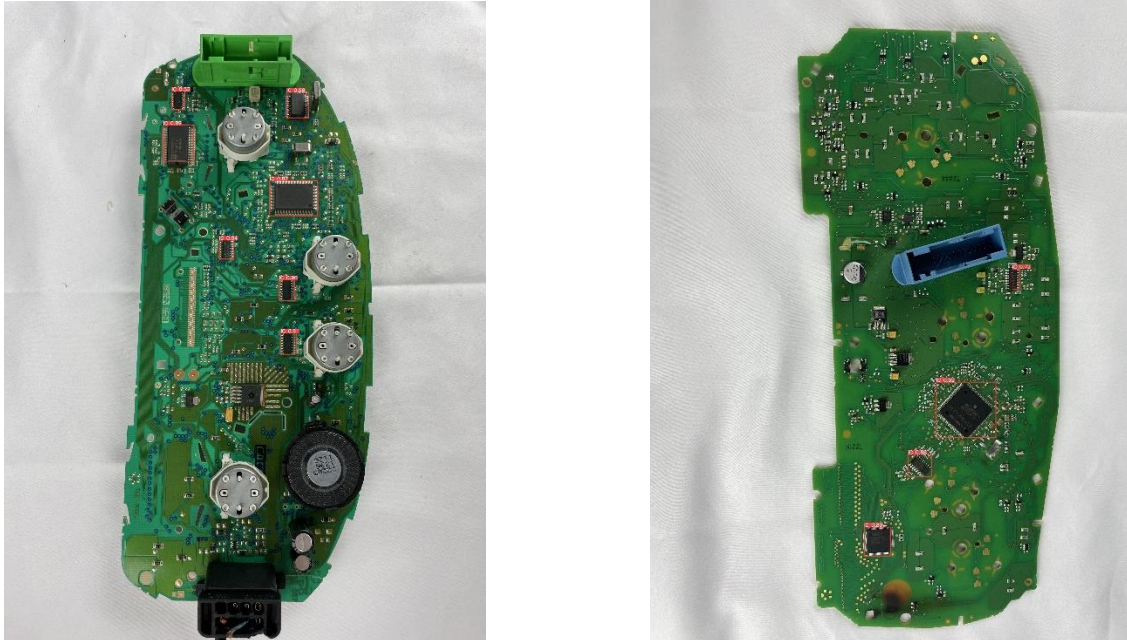


Figure 14. Bounding boxes in red drawn by the AI algorithm on the combi-instrument PCBs

To address this issue, the original image was segmented into nine patches, which were then sequentially fed to the model prior to reconstructing it and reporting on component identification. This method enhanced the identification of all components on the board, but it significantly impacted the real-time capabilities of the algorithm. In fact, the necessity to perform nine inferences per image extended the analysis time to the range of a minute, approximately 45 seconds. Consequently, this required the model to be run offline on a workstation equipped with sufficient computational resources before providing the data to the cobot workstation.

4.3 Safety related features

Another focus of the project in recent months has been safety. Indeed, safeguarding the operator during disassembly operations is not only essential but imperative. Given that the disassembly of electronic boards involves tools that attain high temperatures, and these boards, when heated, can release harmful fumes, it becomes clear why protective measures are crucial to ensure safe working conditions. A primary concern addressed was the potential exposure to toxic fumes during these operations. Instances have been observed, particularly when using the preheating plate, where certain board components reach temperatures near 240 degrees Celsius, begin to melt, and emit potentially hazardous fumes. Due to variations in mass and chemical composition among different boards, it has been noted that not all boards react similarly under heat treatment. In some cases, as mentioned, the heat absorbed by the boards to facilitate the disassembly of TH components is sufficient to generate fume emissions. This phenomenon was further quantified by conducting mass balance measurements with precision scales before and after disassembly activities. Consequently, a laboratory-scale system was

outfitted with a small air filtration system. In a real-world application, with a higher volume of processed material, this system would need to be appropriately scaled to maintain the environment free from any potential risks associated with the release of hazardous fumes. In conjunction with addressing the toxicity risks during operations, efforts have also been directed toward reducing the hazards associated with the cobot system, which is equipped with a potentially hazardous hot end-effector. To mitigate these risks, the approach involved deploying software enhancements by delving into the domain of HRC to enhance the system's intelligence and responsiveness to the operator's presence.

4.3.1 Working area limitations

The initial safety measure implemented involves utilizing the inherent safety features within the software provided by the manufacturer; the cobot's operational program has been configured to confine its working area strictly to the table on which it is positioned, thereby preventing the robotic arm from moving beyond this boundary. By restricting the workspace in this manner, it becomes virtually impossible for the cobot to extend beyond the designated area, thus eliminating the risk of contact with the operator's body. This configuration was achieved using the cobot's Teaching Pendant (TP), where boundaries were established by setting planes that delineate the operational area from the restricted area. The configuration of such planes is illustrated in the accompanying figure 15.

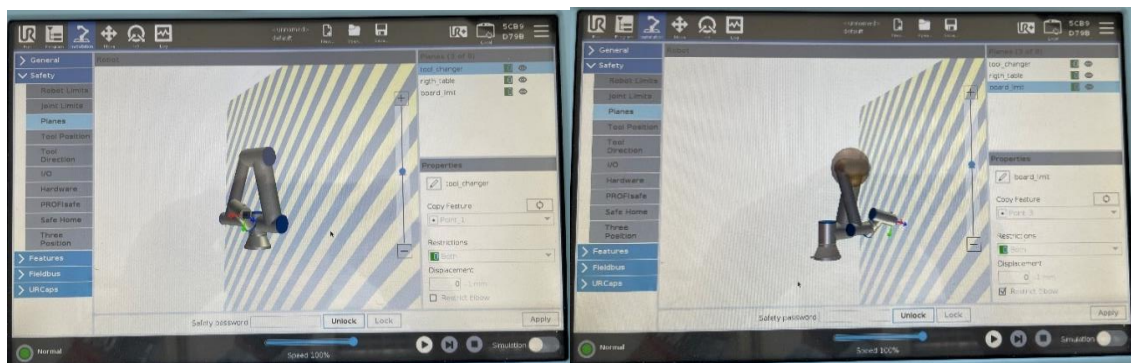


Figure 15. Two of the four planes defined to limit the cobot workspace

4.3.2 Hand detection capabilities

Regarding the second implemented safety measure, efforts were directed toward experimenting with more innovative solutions to enhance security features. This measure was developed in close collaboration with partner SUPSI, which contributed a portion of the source code foundational to the solution. The principal concept involves monitoring the position of the operator's hand relative to the cobot's end-effector, thereby ensuring a maintained distance between them. This approach leverages computer vision, integrates cobot control algorithms, and employs AI, aimed at further investigating the aspects of HRC. The development of this solution originated from the ROS4HRI repository; an open-source platform designed to incorporate human detection capabilities within a robotic operations framework. Specifically, it utilized a model for human hand recognition and pose estimation, which served as the foundational element in the development of this safety measure.

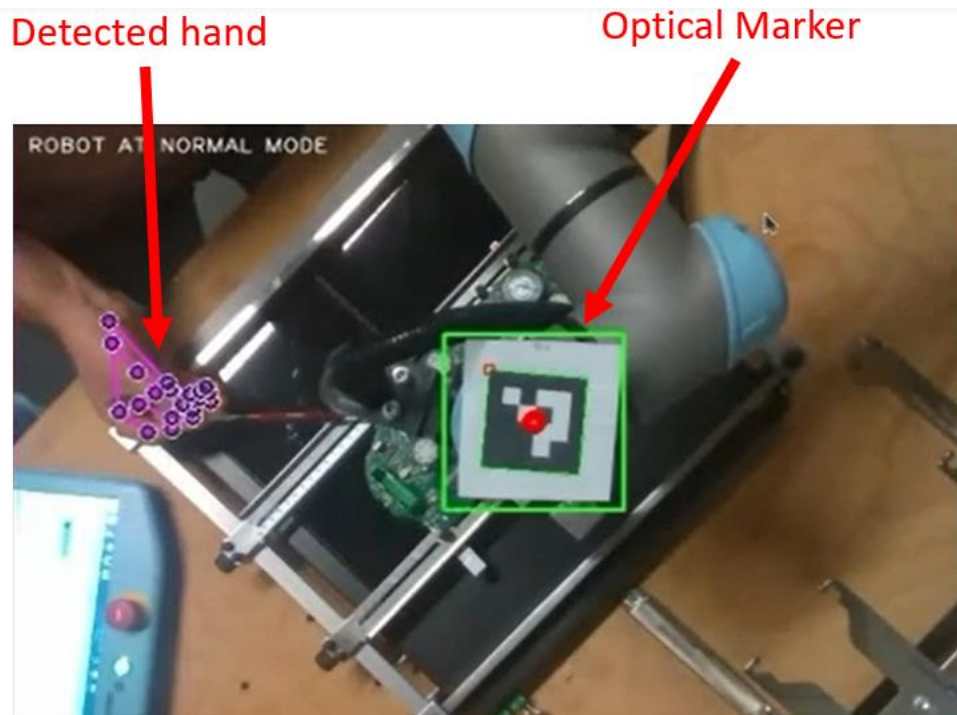


Figure 16. Tracking of operator's hand during disassembly operation

To implement this solution, it was decided to install an Intel Sense D435i camera atop the system to capture the workspace shared between the operator and the cobot. Additionally, an optical marker was placed on joint 5 of the cobot, perfectly perpendicular to the air desolder mounted on the end-effector. This setup enables the algorithm to easily ascertain the position of the robot and delineate its workspace. Subsequently, within the area identified by the AI algorithm as where the operator's hand is located, a corresponding zone representing the actual work area occupied by the operator's hand was defined. Once established, the algorithm calculates the distance between the work area of the hot end-effector and the operator's hand. In the event of any overlap, the algorithm dynamically adjusts the cobot's position to move away from the operator's work area, thereby ensuring the workspace is shared safely. Although this experimental solution was not tested during the training sessions with the operator, since it was developed in the final months of the project, it represents an innovative approach to mitigating the risks associated with space sharing between operators and cobots, especially when cobots are equipped with potentially hazardous tools.

4.3.3 Remarks on the safety solutions implemented

The solutions presented in the previous sections encapsulate the efforts made in implementing safety measures for cobot applications using potentially dangerous tools. Although quantifying the effectiveness of these solutions numerically is challenging, laboratory tests have shown that adopting these measures makes collisions between the tool and the operator highly unlikely. By limiting the cobot's operational area, it becomes impossible for the tool to leave the designated area and come in contact with the operator's body. In the operational area where potential collisions are more conceivable, the implemented solution enables constant monitoring of the operator's hand, preventing accidental contact due to operator inattention. The use of innovative solutions, such as operator hand tracking, represents a significant advancement in the shared workspace between humans and machines, allowing for flexible solutions that protect the operator from potential risks. However, for these solutions to be implemented

outside of a laboratory context, they require certification, particularly regarding system response times. In the presented solution, the response time is approximately 0.2 seconds, a swift interval that nonetheless must be reduced to achieve the real-time performance essential for this type of application.

4.4 Pipeline of the semiautomated disassembly process

The creation of this second configuration involved a thorough examination of the compromises observed in previous disassembly methods presented in D5.1 and D5.2. The learning process introduced in D5.1, while versatile under an experienced operator, poses challenges for beginners. Errors, especially in the positioning of the end-effector, are common with imprecise placement. Conversely, the procedure outlined in D5.2 seeks to simplify the process for the operator during the disassembly procedure; however, it proves inefficient due to the necessity of disassembling all components from the PCBs. The primary bottleneck in the disassembly procedures arises from the requirement to remove some TH components from the PCBs. As extensively discussed, the complexity involved in detaching this type of component necessitates heating a substantial portion of the board to facilitate component removal. The extensive time needed to heat such a large area of the board significantly impairs the disassembly time, thereby diminishing the system's overall performance. In recent advancements reported from the pilot plant, efforts have been directed towards enhancing the intelligence and cognitive capabilities of the cobot system. This enhancement enables the selective targeting of only certain SMDs components considered more valuable, thereby aiming to improve performance specifically in the disassembly phase of SMDs components. Regrettably, the necessity of disassembling TH components from the PCBs is underscored by their high content of valuable, particularly within connectors; consequently, the process has been divided into two distinct phases: the first phase is designed to remove SMDs components efficiently from the board, leveraging the innovative technologies developed throughout the project. The second phase, conversely, focuses on the removal of TH components using a more traditional and operator-intensive approach. These two phases collectively constitute the final pipeline of the disassembly process, which will be detailed in the subsequent sub-sections.

4.4.1 SMD components disassembly

In this stage, the operator, assisted by the cobot (cobot), undertakes the disassembly of SMDs components identified by the computer vision algorithms discussed in previous sections. This segment of the procedure exemplifies an innovative and experimental approach to the disassembly of electronic components, serving as a pilot platform for the development of future technologies in this domain. It is important to note that the analysis conducted by the computer vision algorithms, due to the substantial computational demand, is performed offline on a specialized workstation delineated in section 3.3.5. Following this analysis, the data, which include the information and coordinates of the targeted components, are conveyed in a .txt file to the workstation tasked with controlling the cobot. At this stage, the data are precisely interpreted to navigate the cobot through the disassembly process, guiding the air-desolderer of the coordinates of the detected components. The steps constituting the disassembly procedure are as follows:

1. The operator retrieves the board and positions it on the designated holder.
2. The operator confirms the accuracy of the target components identified by the algorithm designed to identify tantalum capacitors, by eliminating any false positives.

- The operation commences with the cobot positioned over the identified components, bot tantalum capacitors and ICs, while the operator, equipped with a small spatula, assists in detaching them from the board.

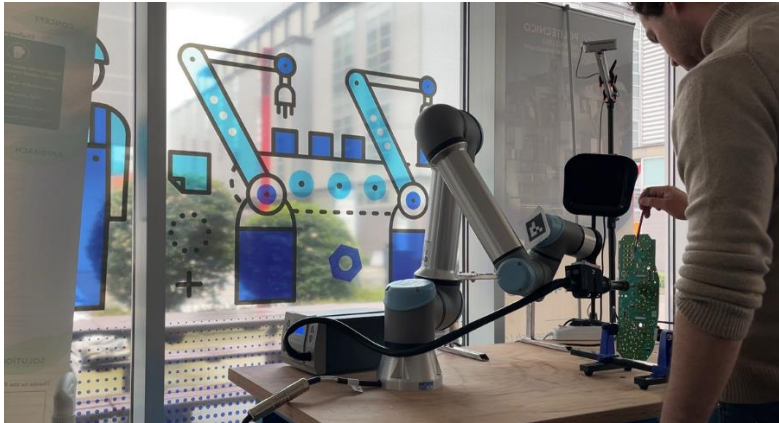


Figure 17. Semi-automated procedure of removal of SMD

The duration of the process varies according to the type of board being processed. The computer vision algorithms take approximately forty-five seconds to identify electronic components on the specialized workstation. The subsequent disassembly time, as previously noted, is heavily dependent on the number and size of the components identified, with times ranging from five seconds for smaller components to twenty seconds for larger ones. Additionally, power consumption is also influenced by the nature of the board; it was calculated based on the value observed across the boards coming from the combi-instrument. Specifically, the average power consumption for the disassembly of SMDs components was approximately 0.2 kWh per processed board. This value accounts for the consumption of both the cobot and the air desoldering equipment attached to it. In the tables below are reported energy consumption data in details for the disassembly of the SMDs components from the combi-instrument of the three Seat models; the disassembly metrics are also included inside the TREASURE Platform:

Ibiza IV series:

Sub-operation	Energy Consumption (kWh)
Robot Energy Consumption (kWh)	0.137
Integrated Circuit IC1 (kWh)	0.0024
Integrated Circuit IC2 (kWh)	0.0096
Integrated Circuit IC3 (kWh)	0.0023
Integrated Circuit IC4 (kWh)	0.0034
Tantalum Capacitor TA1 (kWh)	0.0011
Tantalum Capacitor TA2 (kWh)	0.0013

Leon II series:

Sub-operation	Energy Consumption (kWh)
Robot Energy Consumption	0.099
Integrated Circuit IC1	0.0032
Integrated Circuit IC2	0.0021
Integrated Circuit IC3	0.0024
Integrated Circuit IC4	0.0024

Integrated Circuit IC5

0.0022

Ibiza V series:

Sub-operation	Energy Consumption (kWh)
Robot Energy Consumption (kWh)	0.212
Integrated Circuit IC1 (kWh)	0.0023
Integrated Circuit IC2 (kWh)	0.0046
Integrated Circuit IC3 (kWh)	0.0028
Integrated Circuit IC4 (kWh)	0.0078
Integrated Circuit IC5 (kWh)	0.0021
Integrated Circuit IC6 (kWh)	0.0023
Integrated Circuit IC7 (kWh)	0.0022
Tantalum Capacitor TA1 (kWh)	0.0015

4.4.2 TH components disassembly

The procedure for the removal of TH components has remained consistent with that described in deliverable 5.2. This stage is identified as the most critical within the disassembly process, largely relying on the direct involvement of the operator. Although trials involving the use of a cobot to remove TH components have been conducted, they have not produced significant results. A primary challenge is determining the precise timing when a component is sufficiently hot to be desoldered from the PCBs; this is notably complex due to the variability in how components on the hotplate absorb heat. The readiness for removal largely depends on the specific characteristics of the board, such as its mass and heat absorption capacity, which are not uniformly distributed across the board and unless a large number of thermo-couples are placed or infra-red vision systems are used, it is complex to determine the exact temperatures of components. This discrepancy sometimes causes the cobot to attempt removing components that are not fully desoldered, risking the integrity of the entire PCB by tearing it apart from his fixturing system. In contrast, by involving an operator in the disassembly process, there is an advantage of human sensitivity to discern whether a component has been perfectly desoldered. The procedure is as follows:

1. The operator positions the board on the board fixturing system and places thermos-couples on the surface of the PCB.
2. The operator activates the preheating plate and waits approximately 10 minutes until the desoldering temperature is reached (approx. 220 degrees Celsius).
3. The operator, using tongs or pliers, removes manually the TH components from the board



Figure 18. Removal of TH components

The disassembly times are contingent upon the specific characteristics of the board, for which an average was calculated based on the PCBs examined. The average disassembly time is approximately eleven minutes, with an associated power consumption of around 3 kWh, predominantly attributable to the pre-heating plate. Analysis of these figures underscores the significant impact that this methodology has on the efficiency and energy consumption of the overall solution. This highlights the ongoing need for research in electronic component disassembly to enhance operational efficiencies and reduce energy usage.

5 Training of POLLINI operators

5.1 Scope of the training

The scope of the training activities developed as part of the TREASURE project aims to test and validate the pilot plant solution for the semi-automated disassembly of PCB boards. This initiative seeks to bridge the gap between advanced technological frameworks and practical, on-the-ground operations in recycling plants. By engaging directly with dismantlers who are the field experts the project endeavours to garner invaluable feedback that will refine and enhance the pilot solution. Moreover, this training initiative serves as a platform to acquaint these professionals with key Industry 4.0 technologies, fostering a deeper understanding and familiarity with cutting-edge solutions in recycling practices. The comprehensive training program is structured into three distinct sessions, each designed to progressively introduce participants to various facets of the technology and its application in their work environment.

5.2 Training sessions

The training program is thoughtfully structured to encompass three critical sessions, each meticulously designed to facilitate a systematic and gradual acquisition of essential skills, as well as familiarity with advanced technological tools. Prior to the hands-on operator sessions, a preliminary session with managers takes place, aimed at pre-validating the training content and process. This foundational session ensures the alignment of the training with organizational objectives and operational needs, and secures managerial buy-in, which is essential for a successful training outcome. Following this initial managerial engagement, the first of the two operator-focused sessions introduced the participants to the innovative concept of collaborative robots (cobots). This session underscores the pivotal differences and advantages of cobots when compared to traditional industrial robots. Special emphasis is placed on their flexibility, inherent

safety features, and the unparalleled capacity for human-machine collaboration. This structured approach ensures that participants not only gain a thorough understanding of the theoretical underpinnings of cobot technology but are also well-prepared to leverage these insights in practical applications, setting a solid foundation for the more advanced, hands-on training that follows.

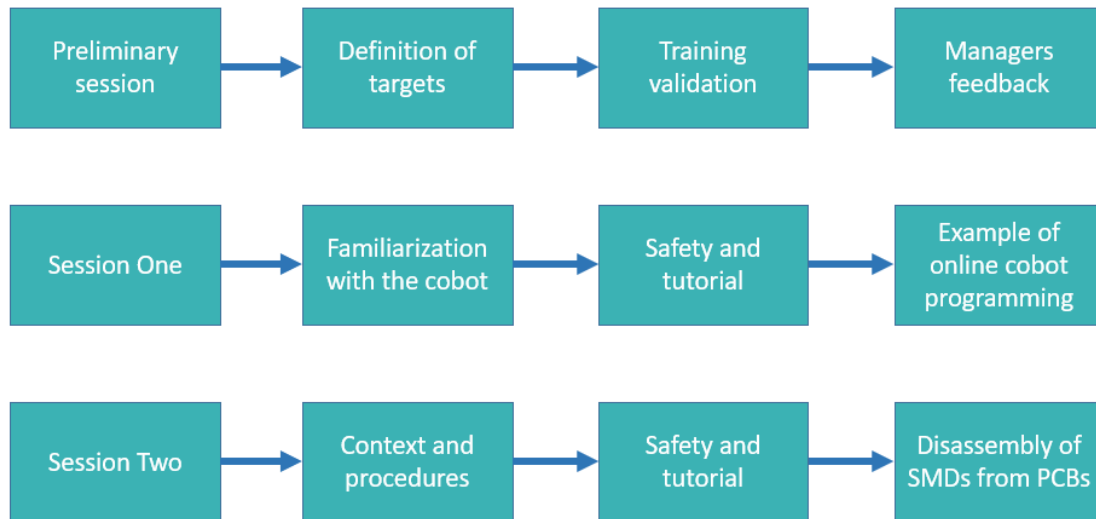


Figure 19. Structure of the training sessions

5.1.1 Preliminary session

The incorporation of a preliminary session, carried out on the 3^o of October 2023, with management before launching the operator training sessions for semi-automated PCB disassembly is a crucial strategy that enhances the training's effectiveness. This initial meeting focuses on aligning the upcoming training with the organization's objectives and leveraging managerial insights to refine the training's scope and content. By doing so, it ensures that the program addresses real operational needs and challenges, fostering a curriculum that is both relevant and practically applicable. Managerial involvement at this early stage not only secures essential support and resources but also encourages a proactive approach to change management. This is particularly important as the shift towards semi-automated processes represents a significant transformation in operational workflows. Managers' insights into team dynamics and individual skill gaps allow for the customization of the training program, making it more targeted and effective. Additionally, this preliminary session acts as a platform for managers to highlight specific areas for emphasis, thereby ensuring the training is closely tailored to the practical realities of the workplace. The focus of this session was to define and adapt the steps of the training sessions with operators to the operators' prior knowledge, trying to find the right balance between theory and practice to provide the correct input information to approach the topic of disassembly of electronic components using most effectively a semiautomated solution. As a result of this, the manager was able to experience firsthand some of the activities carried out later by the operators, especially the parts related to the introductory section of familiarization with the cobot concept being able to collaborate in the definition of the proper educational activities for the training session dedicated specifically to the pilot plant.



Figure 20. Pollini's manager interacting with the cobot in the Industry 4.0 Laboratory at the Politecnico di Milano

This foresightful planning facilitates a smoother transition to new technologies, mitigates potential resistance, and enhances overall adoption rates. In summary, a pre-validation session with management is not just beneficial but essential for aligning the training with strategic goals, optimizing its relevance, and ensuring a cohesive approach to adopting semi-automated disassembly processes. This strategic alignment maximizes training impact, driving operational excellence, and fostering the successful integration of innovative recycling technologies.

5.1.2 Session one

This session, carried out on the morning of the 9^o of November 2023, covers the basics of cobot operation, safety protocols, and an introduction to online programming examples, setting a foundational understanding necessary for hands-on activities. Cobots represent a paradigm shift in robotic technology, designed for direct interaction with human operators within a shared workspace. Unlike their predecessors, cobots are built with an emphasis on flexibility and safety, featuring impedance control systems to detect contact and halt operations immediately, thus ensuring operator safety. Additionally, the manual-guidance feature allows operators to intuitively position the cobot, demonstrating the user-friendly nature of this technology. A manual tool change activity was also performed so that the operator could perform hands-on experience of a routine task performed on the cobot. The manual tool change was also included to demonstrate how these activities, although easily performed by an operator, can also be performed automatically while saving considerable setup time.



Figure 21. Pollini's operator performing a manual tool change operation equipping the robot with a two-finger electric gripper.

These features are explored in detail during the training, with practical demonstrations to solidify understanding. The application of cobots in tasks such as soldering, pick-and-place, palletizing, assembly, screw driving, and quality control is discussed, showcasing their versatility. A significant portion of the training is dedicated to programming the cobots using a teach pendant, highlighting the ease of use for both industrial and research applications. A practical tutorial on the teach pendant focuses on a pick-and-place task, breaking down the problem and engaging participants in the programming process.

5.1.3 Session two

The second session of the structured training, carried out on the afternoon of the 9th of November 2023, delves into sophisticated technologies like hand-eye systems and computer vision, underscoring their essential roles in enhancing the precision, efficiency, and safety of the disassembly process. This session, integral to the training program, aims to equip operators with the skills and knowledge to adeptly manage and operate these systems within the context of PCB disassembly. At the core of this session is the exploration of hand-eye systems, a technology that synergizes the capabilities of robotic arms (cobots) and advanced vision systems to perform intricate tasks such as component identification and precise manipulation. The session introduces the concept of computer vision, a field that enables machines to interpret and understand the visual world. Through detailed discussions and demonstrations, the training elucidates how these technologies are employed to identify, sort, and disassemble components from PCBs, showcasing their application in the TREASURE project. A significant portion of the session is dedicated to presenting a proposed pilot plant model that integrates computer vision (CV), artificial intelligence (AI), and collaborative robotics (cobots) in the PCB disassembly process. This model illustrates the estimation of material value in PCB components, the further disassembly of critical components, and the routing of dismantled components based on their chemical composition, all facilitated by AI and CV technologies.



Figure 22. Pollini's operator during the explanation of the computer vision solutions.

Training activities are meticulously designed to provide hands-on experience with AI and computer vision solutions; these activities include testing the AI solution through transfer learning, which underscores the adaptability and efficiency of pre-trained models in identifying and classifying PCB components. Furthermore, the session delves into computer vision tests, such as background removal, high-resolution imaging acquisition, component bounding box identification, and patch extraction, illustrating the process of image analysis and component selection.

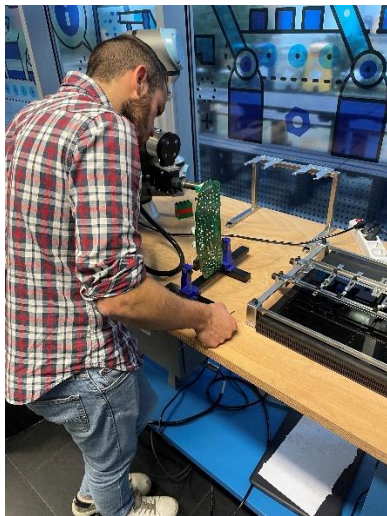


Figure 23. Pollini's operator testing the cobot and the pilot plant for semi-automated PCB disassembly.

Operators are also engaged in validating the operator assistance system, ensuring they are proficient in interfacing with the technology and can effectively leverage it in the disassembly process. The session's hands-on approach, coupled with theoretical insights, ensures a comprehensive understanding of the hand-eye system and computer vision applications, preparing operators for their crucial roles in semi-automated PCB disassembly. The second session of the training program marks a significant step forward in preparing operators for the challenges and opportunities presented by semi-automated PCB disassembly. By focusing on hand-eye systems and computer vision technologies, the session provides a deep dive into the

future of electronic recycling, where technology and human expertise converge to create safer, more efficient, and sustainable recycling processes

5.3 Results and feedback

Concluding our assessment of the TREASURE project's pilot plant associated training activities, it's evident that while the pilot plant is at a developmental stage with a Technology Readiness Level (TRL) not yet suitable for full-scale production, these exercises have served as a crucial benchmark for identifying potential enhancements. The training sessions have illuminated paths for refining the usability and effectiveness of the solution, confirming the value of integrating advanced technologies such as collaborative robotics, pose estimation systems, and machine vision solutions into recycling processes.

Feedback from the training sessions, particularly from operators inexperienced with such sophisticated systems, has been instrumental in understanding the end-user perspective. This direct engagement has underscored the importance of aligning semi-automated solutions with human operators' capabilities and needs. The practical application of these technologies, under the guidance of real-world operators, has brought to light the essential adjustments needed to design these systems more accessible and user-friendly. Key feedback themes include:

- **Intuitive Interfacing:** A recurring suggestion is the need for more intuitive interfaces that simplify the interaction between the operator and the technology. Streamlining command inputs and making system feedback more understandable can significantly reduce the learning curve and enhance operational efficiency.
- **User-Centric Design:** Operators highlighted the importance of designing systems that prioritize the user's comfort and ease of use. This includes ergonomic considerations in the physical design of equipment and user interfaces that accommodate varying levels of technical proficiency.
- **Adaptive Systems:** There is a call for systems capable of adapting to different operators' skill levels, offering customized guidance and assistance. Such adaptability could be achieved through AI-driven interfaces that learn from each interaction to provide more personalized support.
- **Practical Training:** The effectiveness of hands-on training sessions was universally acknowledged, with operators appreciating the opportunity to directly interact with the technologies. This hands-on approach should be expanded, offering more scenarios and challenges that mirror real-world conditions.

In conclusion, the pilot plant and its accompanying training activities have laid a strong foundation for further development. The insights gained from this phase are invaluable, offering a clear directive to make technological interfaces more intuitive and user-friendly. Emphasizing these improvements will ensure that the solution not only enhances efficiency but also becomes a genuinely supportive tool for operators, alleviating the burdens of repetitive and physically demanding tasks. Integrating these feedback loops into the development process will be pivotal in achieving a solution that is both technologically advanced and deeply attuned to the human element of recycling operations.

6 Future work and Conclusions

6.1 Technological barriers and mitigation actions

During the project's development and the subsequent theorization of an efficient model for semi-automated disassembly of PCBs components, certain technological and non-technological

constraints became evident, impeding the full realization of the original concept. The framework outlined in Section 4.1, if properly executed, would allow for selective and targeted disassembly of specific components from PCBs, thereby facilitating the recovery of CRMs contained in these specific components. The limitation does not lie in the technical feasibility of the solution but in the difficulty of obtaining data with adequate volume and granularity. For effective selective disassembly, large datasets containing information regarding the macro-categories of components (such as capacitors, inductors, and resistors...) but also providing granular characterization of individual components. This challenge restricted the identification of electronic components to those for which adequate data is available for training machine learning models. During the project, it became clear that accessible open-source data containing this information is extremely limited. Additionally creating comprehensive datasets from scratch is a daunting and resource-intensive task, suggesting that the most straightforward approach is to prevent existing information from becoming lost or inaccessible within the automotive electronics supply chain. One of the significant outcomes of the TREASURE project has been to collaborate with UNI-led project partners to propose standardization measures that aim to enhance data transparency provided by Original Equipment Manufacturers (OEMs) concerning automotive electronics. This effort underscores that while certain limitations are challenging to address through technical solutions alone, fostering synergies across multiple levels such as through standardization bodies can help mitigate issues that might otherwise be insurmountable by a purely technical approach.

6.2 Profitability analysis

The availability of secondary CRMs to mitigate supply bottlenecks is limited, and thus increasing CRMs recycling rates is crucial to meet growing demand. WEEE, also known as e-waste, is the largest and fastest-growing waste stream globally, with an estimated volume of around 50 million metric tonnes per year and an annual growth rate of 3-5%. This makes it a significant source of secondary CRMs for a CE and for reusable products/components that contain them. Furthermore, (Charles, R. G., Douglas, P., Dowling, M., Liversage, G., & Davies, M. L. 2020) emphasize the rapid and consistent growth of WEEE volumes due to technological progress, indicating its potential to fully support the disassembly processes needed for recovering CRMs that are currently causing supply bottlenecks. While the implemented solutions presented in this deliverable incorporate several intriguing technological approaches for disassembling circuit boards, the critical challenge remains the throughput of processed materials. Given that the mass of individual disassembled components constitutes a very small percentage of the mass of the entire board, it's crucial for an optimal solution to maximize the volume of boards processed. The material composition of PCBs varies depending on the specific characteristics of each board. In the context of electronic boards from the automotive sector, achieving sufficient material volumes in the near future seems unlikely. This is because most vehicles slated for recycling are obsolete models, with an average lifespan of about fifteen years, and typically contain few electronic components. This observation is primarily quantitative since systematic access to information is restricted. However, the scenario might evolve as more modern vehicles are recycled, given that the electronic content in cars is continually increasing. In contrast, when considering consumer electronics and the corresponding volumes of WEEE generated, the scenario changes significantly, suggesting a potential for greater material throughput in this domain. Estimating the investment required to establish a recycling plant for CRMs recovery is challenging. The profitability of such a plant is closely tied to the feasibility of specific recycling processes for the various materials within the disassembled components and the type of circuit boards processed. Therefore, collaboration with UNIVAQ is underway to select and provide

components for recycling tests at the pilot plant developed in the context of the H2020 FENIX and H2020 TREASURE projects. Given the scarcity of studies on this type of investment, (Ramon, H., Peeters, J. R., Sterkens, W., Duflou, J. R., Kellens, K., & Dewulf, W. 2020) offer valuable insights into a potentially profitable process for tantalum recovery from electronic boards. They indicate that "Based on the assumed and measured values, an internal rate of return on investment in a four-year time horizon and a minimum acceptable rate of return (MARR) of 15% corresponds to a permissible investment of €60,000." This calculation factors in the price of tantalum and an average component removal time of 2.5 seconds. The article also stresses that full capacity and full automation are crucial to achieving reasonable profit margin; the disassembly solution must be adaptable and ensure a steady throughput of processed material. By enabling targeted disassembly operations, a broader range of materials can be recovered, potentially enhancing profitability. This flexibility is particularly important in cases where the focus is exclusively on components containing tantalum, as it allows for a more diverse and valuable recovery process.

6.3 Conclusions and future work

Although the project faced limitations that prevented the implementation of the optimal solution initially theorized, the development of the pilot plant for semi-automated PCBs disassembly underscored the complexity of the problem and the necessity to address it. This pilot plant demonstrated the feasibility of achieving a level of disassembly suitable for the recovery of CRMs from not only automotive electronics but also other electronic components at the end of their lifecycle. Additionally, several new research directions emerged during the pilot's development, indicating potential areas for further exploration. The topic of cobotics was investigated by applying it to a real-world problem and equipping it with cognitive capabilities for autonomous target identification and environmental perception. This approach required intensive development of computer vision algorithms, allowing the cobot to receive coordinates for guiding its movements. Human-robotic collaboration was also explored, focusing on enhanced safety measures through an innovative system to track the operator's hand. The concept of non-destructive disassembly of PCBs was another critical area of study identifying the benefits of this procedure. Furthermore, the developed solutions were tested with industry operators, providing valuable feedback, and expanding the potential applications beyond a laboratory setting. Future work will continue along various paths based on the research avenues explored during the project's development exploring the potential for increasingly flexible and efficient solutions that can support operators in tasks that would benefit greatly from the many synergies possible on semi-automated applications. The primary goal, in the direction to obtain an optimal solution for PCBs selective disassembly, will be to increase the throughput of processed materials at the pilot plant, moving towards more sustainable profitability by scaling the process to an industrial level.

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8 Abbreviations

CE	Circular Economy
EoL	End-of-Life
cobot	Collaborative robots
HRC	Human Robot Collaboration
AGV	Automated Guided Vehicle
CRMs	Critical Raw Material(s)
PCBs	Printed Circuit Boards
SMD	Surface Mounted Devices
TH	Trough-Hole
WEEE	Waste from Electrical and Electronic Equipment
AI	Artificial Intelligence

