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The Challenges of Using Robots to Automate the Recycling of Electronic Devices

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Fig. 1. A batch of heat cost allocators and smoke detectors. The variety of designs and different states of damage make the removal of batteries difficult.

***Abstract*—This paper tackles the challenges of automating battery removal from small electronic devices, such as heat cost allocators and smoke detectors. Safe and efficient removal is essential to mitigate fire hazards posed by lithium batteries in recycling facilities and to support a circular economy. We present advanced methodologies and robotic technologies to address hurdles arising from diverse device designs, complex battery compartments, and varying states of damage. Our approach integrates Vision-Language Models (VLMs) for real-time, adaptive disassembly planning, computer vision, tactile skills, soft robotics, and reconfigurable robotic workcells to enhance perception, dexterity, and adaptability. The resulting workcell with modular hardware and standardized interfaces enables seamless adaptation across device types. Laboratory tests demonstrate higher efficiency and reduced manual intervention, underscoring the potential of AI-driven, reconfigurable robotics for scalable and sustainable e-waste recycling.**

***Index Terms*—Automation of recycling, disassembly, adaptive robots, reconfigurable robotic cells, soft robotics, waste electrical and electronic equipment (WEEE).**

I. INTRODUCTION

THE rapid growth of electronic waste (see Fig. 1) has made the development of efficient and safe recycling strategies a critical environmental and economic priority. Waste Electrical and Electronic Equipment (WEEE) contains a diverse range of materials, including metals, plastics, glass, and ceramics [1], [2]. The metals include common ones such as copper, iron, aluminum, zinc, and tin; toxic metals like lead, cadmium, and antimony; and precious metals such as gold, silver, platinum, and palladium [3]. Recovering and reintegrating these secondary raw materials into the economic cycle is crucial for supporting a circular economy.

Recycling WEEE generally involves several stages including sorting, dismantling, removal of hazardous parts, shredding (cutting, crushing, grinding), and physical separation to extract reusable materials [2], [4]. The removal of hazardous components, such as batteries, occurs prior to the input stage illustrated in Fig. 2, and represents one of the most complex and safety-critical steps in WEEE processing. If not removed properly, lithium-ion batteries (LIB) can be physically damaged during shredding, potentially leading to short circuits and fires due to thermal runaway. Fires caused by damaged batteries are a well-documented hazard in WEEE recycling facilities, often resulting in significant equipment damage, operational downtime, and safety risks for workers. The best way to prevent the occurrence of such LIB-caused ignition and other incidents is to avoid crushing/shredding LIBs in WEEE [5]. WEEE free of hazardous materials is then fed into a pre-shredder to break the devices down into smaller pieces.

Shredded material undergoes pre-separation, which includes sorting into plastics and various metals. Pre-separated materials are further processed in a hammer mill, grinding them into smaller pieces. Exhaust air from the hammer mill is filtered to remove dust, which is collected separately. Ground material passes through a magnetic separator to remove steel. Remaining material goes through an eddy current separator to separate non-ferrous concentrates. Finally, non-ferrous concentrates undergo another round of grinding in a hammer mill. Material is sorted based on its properties, separating it into non-ferrous concentrate and plastic fraction (cf. Fig. 2). The specific processes used depend on the type of WEEE being processed. While many stages are automated, some steps – especially dismantling and hazardous material removal – still require human intervention or supervision.

The removal of hazardous components from WEEE, such as batteries, remains a significant challenge for the recycling industry [6]. This process is hazardous and therefore diffi-

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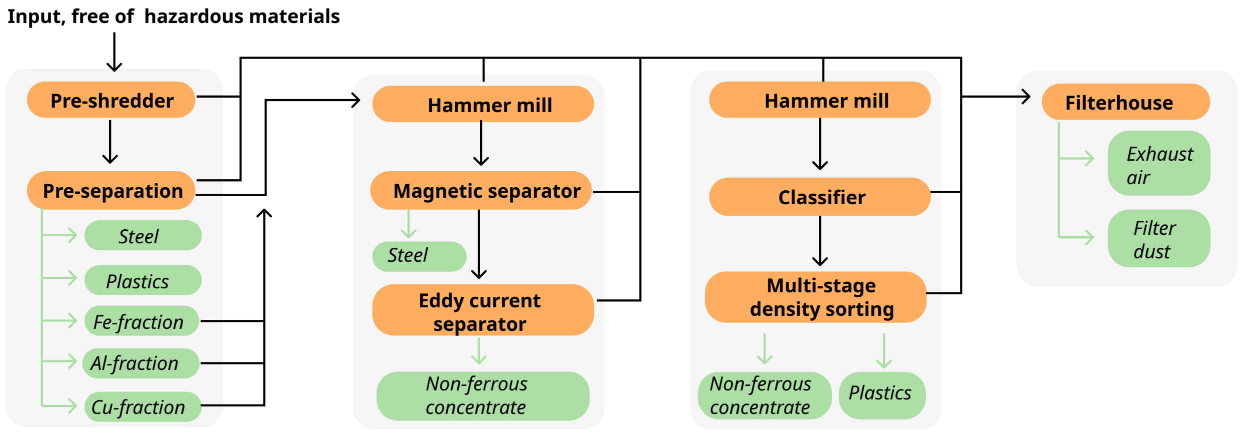


Fig. 2. Typical recycling processes in a WEEE recycling plant

cult to automate. While the importance of disassembly for recycling has been acknowledged and explored in various contexts, robotic disassembly has yet to make a significant impact on WEEE recycling, despite the development of a few prototype systems [7]. General guidelines to address the flexibility and reconfigurability challenges in handling varying sizes of components from electrical vehicles were provided by Li et al. [8]. Some example processes where robots were utilized include the disassembly of battery packs and phones, but significant challenges remain. The main issue is that the systems proposed to date do not deal with a wide range of different devices encountered in WEEE recycling.

Despite increasing automation in later recycling stages, early disassembly steps remain a major bottleneck. This paper addresses that gap by focusing on the methodologies and advanced robotic technologies that can be applied to remove batteries from a variety of small electronic devices, such as heat cost allocators and smoke detectors (see Fig. 1). For these types of devices, the initial dismantling and removal stage is essential to eliminate lithium batteries, which are the primary cause of fires in WEEE treatment facilities, posing serious risks to equipment, workers, and the environment [9].

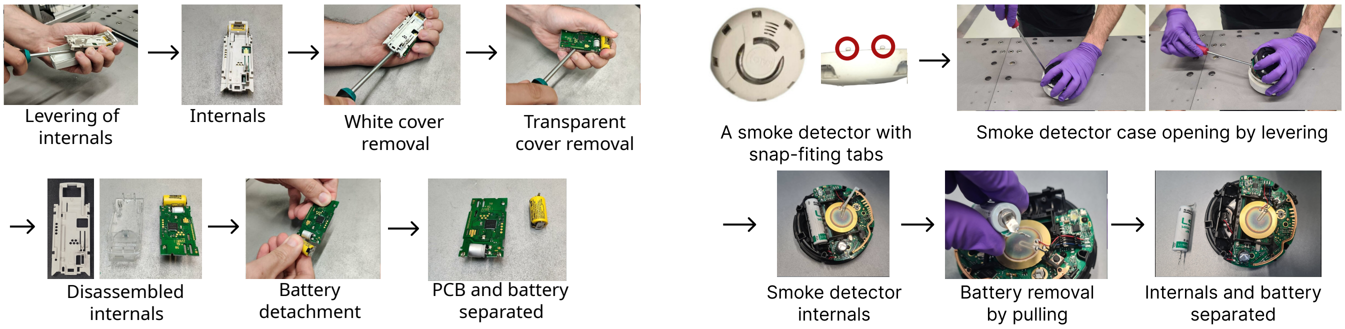
II. CHALLENGES OF BATTERY REMOVAL

Removing batteries from electronic devices like heat cost allocators (HCAs) and smoke detectors (SDs) is challenging for robots. Firstly, the variety of designs poses a significant challenge. Electronic devices come in various shapes and sizes, as shown in Fig. 1, each with different battery compartments and mechanisms to access them. Additionally, in many cases, these devices are not designed to be easily opened and the batteries are soldered directly to the device, making removal even more complex. The non-standardized nature of these designs means that each device requires a different approach to open and remove the batteries. Dealing with varying states of device damage is another challenge. These issues prevent us from programming robots to disassemble the devices in a traditional manner. Instead, the disassembly sequences need to be created on the fly, taking into account the specific design and state of damage of each device.

The precision, dexterity, and force control required to remove batteries are significant hurdles. The dismantling process demands advanced tactile motor skills, precise manipulation, and the ability to apply the correct amount of force, which can be challenging for robots to achieve. Furthermore, the process involves different angles and forces to open compartments and extract batteries, requiring a high degree of adaptability. The use of reconfigurable and adaptive fixtures, where a variety of devices can be securely mounted, is essential to allow robots to apply the necessary forces accurately.

The wide variety of device shapes and sizes in WEEE presents a significant challenge for robotic grasping. Traditional rigid robots, though effective in standardized industrial settings, often struggle in unstructured environments such as e-waste disassembly, where flexibility and adaptability are crucial. Soft robotics offers a promising solution by enabling safer and more versatile manipulation of complex, delicate components. Notable examples include a pneumatically actuated continuum robot capable of navigating cluttered spaces [10]; elastomer-based grippers designed for gentle, adaptive grasping of irregular objects [11]; and a soft robotic tentacle developed for precise and compliant interaction in constrained environments [12]. These systems, although not originally designed for e-waste, have proven effective in handling fragile items in diverse domains such as biomedical applications, agriculture, and search-and-rescue, where similar manipulation challenges exist. The capabilities demonstrated in these domains – such as navigating confined spaces, delicately grasping irregular or fragile objects, and adapting to environmental variability – are directly relevant to the requirements of battery removal in WEEE disassembly. Tasks like extracting lithium batteries without damaging them share similar constraints to handling soft biological tissues or fragile agricultural produce, reinforcing the suitability of soft robotic grippers for this context.

By conforming to the shape and texture of target objects, soft robotic grippers can reduce the risk of damage while improving grasp stability. This makes them particularly well-suited for the careful extraction of fragile and hazardous components like batteries. Such grippers can improve the robot's ability to grasp and manipulate a variety of parts, which



(a) Heat cost allocator disassembly

(b) Smoke detector disassembly

Fig. 3. Steps for manual disassembly of different WEEE. Internals become accessible after removing the external casing. Deformable tabs (in the red circles) make up the snap-fitting used to hold the casing parts together (b). Sometimes additional steps are necessary to gain access to the battery (a). Note, that batteries are connected to the PCBs in different ways.

enhances the overall efficiency of the recycling process. While it is not a problem if the device itself is damaged during the disassembly process, robots must be able to perform these tasks without causing damage to the battery.

Reconfiguring robotic workcells for different devices is also essential to handle the diversity in electronic device designs. Disassembly cells for recycling must be equipped with mechanisms that allow them to be reconfigured quickly and efficiently to accommodate various devices. This includes adjustable fixtures and adaptable tools that can be modified or replaced to suit the specific requirements of each device. Integrating such reconfiguration mechanisms into the disassembly workcell ensures that a robot can handle a wide range of tasks without extensive downtime, improving the overall productivity and flexibility of the recycling process.

The complexity of battery compartments further complicates the task for robots. Many battery compartments are secured with screws, latches, or covers that need precise handling to open. In some cases, the devices can only be opened through destructive operations, which requires a level of precision and dexterity that is difficult for robots to achieve. This creates significant safety concerns because incorrect handling can damage the battery, potentially causing leakage or other hazards. One possible solution to address these issues is to add special machines and tools to support different actions involved in the disassembly process, such as cutting, but the design of such machines and tools is again made difficult by a large variety of devices that need to be processed.

Sensing and perception challenges also play a role in the difficulty of this task. Robots need to accurately identify the type of device, its location, the main features of the battery compartment, and the mechanisms to open them. Handling small parts, such as screws or clips, requires precise handling, which can be challenging for robotic grippers and sensors. The variability in environmental factors, such as different lighting conditions, space constraints, and orientations, further complicates the perception tasks.

To address these challenges, AI is crucial to create robust disassembly programs on the fly. An AI system should analyze the specific design and condition of each device in real-time and generate customized disassembly sequences that account for unique features and potential damage. This dynamic adaptation is essential for managing the wide variety of designs and states of wear and tear in electronic devices. The integration of AI with robotic systems can enhance perception, dexterity, and decision-making in disassembly processes, enabling robots to efficiently and safely remove batteries from a variety of electronic devices. Without significant advancements in robotic dexterity, skill learning, perception, adaptability, and AI-driven intelligence, these tasks are viable only for specific devices that can be analyzed beforehand while general solutions remain exceedingly difficult.

III. KEY ROBOTICS TECHNOLOGIES

We propose to overcome the challenges of battery removal in electronic devices by exploiting advanced technologies that enable robots to handle diverse designs, varying states of damage, and complex battery compartments. Artificial intelligence, particularly through computer vision and large vision-language models (VLMs), enables robots to interpret different device structures and generate adaptive disassembly strategies in real-time by integrating visual data and textual context. High-frequency tactile feedback and precise force-impedance control enhance robotic dexterity, allowing for adaptive and efficient manipulation of different components. Soft robotics, with its flexible and compliant grippers, ensures secure handling of diverse parts while minimizing the risk of damage. Furthermore, modular and reconfigurable robotic cells provide the adaptability necessary to process a broad range of devices, ensuring seamless transitions when disassembling different device types. Together, these technologies address the inherent complexity of electronic waste recycling, paving the way for safer, more efficient, and scalable battery removal solutions.

A. *Computer vision and large vision-language models*

The disassembly of electronic devices for battery removal can generally be divided into sequential sub-tasks. Traditionally, the desired sequences are either manually programmed or generated semi-automatically using planning algorithms, based on descriptions such as Planning Domain Definition Language (PDDL). However, such approaches are insufficient

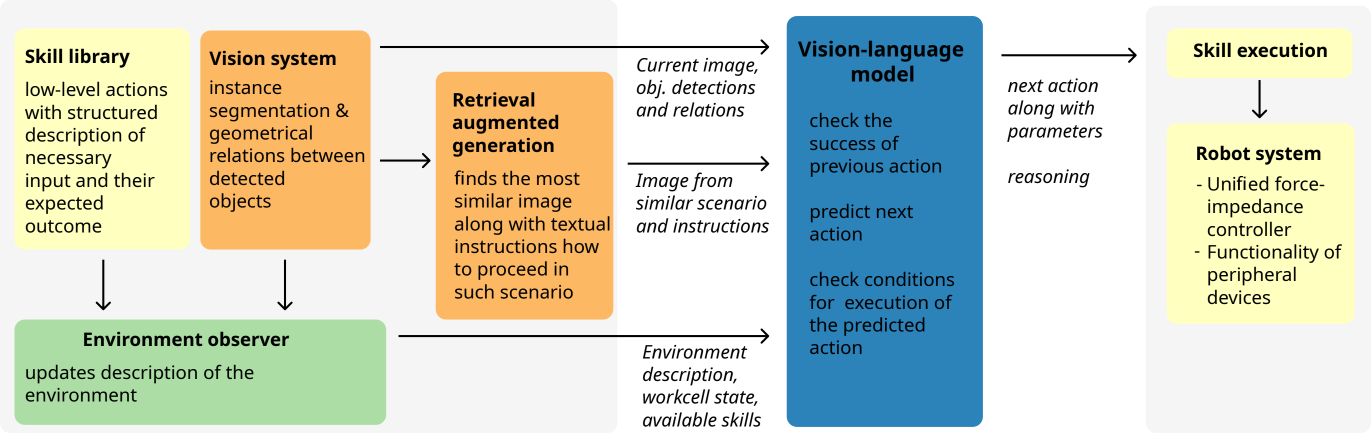


Fig. 4. VLM-based action prediction workflow.

in dynamic environments and for a large variety of devices, where discrepancies between the devices and the actual and expected environment states may lead to failure. Moreover, manual domain specification can be time- and programming-intensive.

To address these challenges, we developed an approach for action prediction and monitoring based on natural language textual instructions and visual inputs from an RGB-D camera. Our methodology involves the design of an action prediction pipeline utilizing a Vision-Language Model (VLM), an auxiliary object detection model, and a library of adaptive manipulation skills for dismantling of electronic devices (e.g., cutting, levering, object grasping, etc.).

In the proposed framework, VLMs are employed for monitoring, that is to evaluate the success of the previously executed manipulation actions, and prediction of the next disassembly step given a current snapshot of the device and textual instructions (as illustrated in Fig. 4). Integration with PDDL is utilized to ensure logical consistency of the predicted actions. The output of visual processing and PDDL environment description are used to create a list of available actions and update the environment state after each action has been taken. Additionally, Retrieval-Augmented Generation (RAG) [13] technique is used to retrieve relevant examples based on input images and text from an example database. This way we enable few-shot learning that leads to improved predictions without the need for VLM retraining.

The key advantage of the proposed approach compared to standard expert systems for planning and monitoring is that the programmer can avoid explicitly specifying a course of action for all possible situations that can arise in device disassembly. The system can generalize across similar devices and propose the correct course of disassembly steps provided that the descriptions provided through RAG and the available disassembly actions suffice to perform the desired task.

1) Methodology: To ensure that the VLM considers only actions that a robot can execute, we first specify a library of available disassembly operations (skill library in Fig. 4). These include grasping, pick-and-place motions, levering, cutting, rocking motion to dislodge batteries hardwired to PCBs, CNC milling, tool exchange operations, etc. Each operation is associated with a textual description that provides detailed information about its use. Each adaptive skill is mapped to a PDDL operator, which includes execution preconditions, a set of input arguments (objects), and defined postconditions. This enables the system to enforce logical constraints, such as preventing CNC cutting unless the object is clamped in the CNC mill.

At runtime, an auxiliary visual routine based on YOLOv8 object detection and classification updates the symbolic environment. This includes identifying currently visible devices, their parts, and inferred spatial or functional relationships (e.g., “PCB within the heat cost allocator”). The resulting environment description constrains the action space passed to the VLM, which ensures that only valid actions are proposed and reduces hallucinations.

After each action is executed, both the action and its arguments are appended to a list of prior actions, which is included in subsequent VLM prompts. This allows the VLM to retain temporal context and reason about the evolving task sequence. If an action is deemed successful, its effects are applied to the PDDL environment representation. This symbolic update complements visual information and is particularly useful when certain state changes, such as a cover being removed, are difficult to confirm visually but can be logically inferred from successful execution.

The determination of success is based on two criteria: (1) successful completion of the low-level motion plan, and (2) a visual result that sufficiently matches known positive examples of the desired outcome, in contrast to known failure cases. Importantly, success does not require perfect execution; instead, it encompasses a range of acceptable outcomes that confidently reflect the intended effect and allow safe symbolic state updates.

To improve the VLM’s response accuracy, we use Retrieval-Augmented Generation (RAG). Compared to fine-tuning, RAG is less resource-intensive and avoids risks such as catastrophic forgetting. We construct a local knowledge base of images, each paired with a manually written set of relevant question–answer pairs. These images are encoded using CLIP [14]

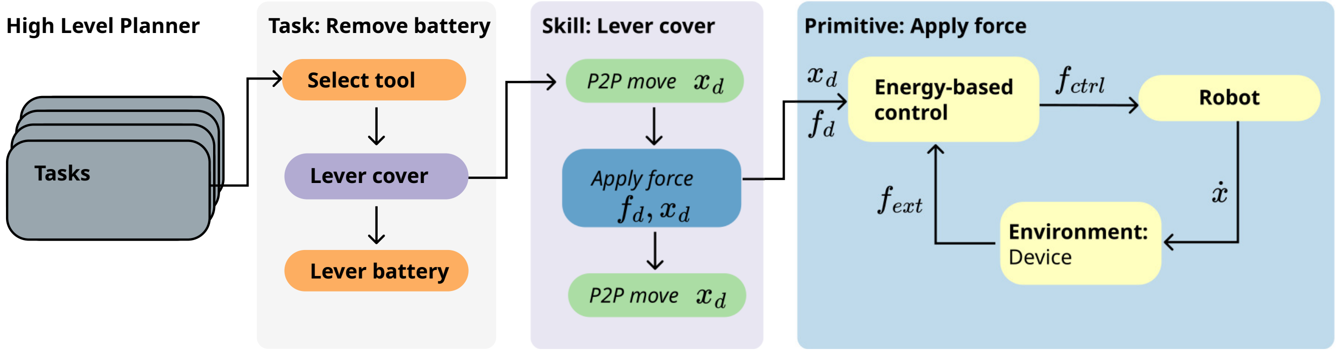


Fig. 5. Hierarchical decomposition of the robotic battery removal task using tactile skills with adaptive control. At the task level, decisions are made on which skills to employ for dismantling the device, leveraging a library of tactile skills. At the skill level, action *Lever cover* is decomposed into point-to-point (P2P) motion and force application, while at the primitive level, unified force-impedance control (UFIC) ensures compliant and stable interaction with the environment. Utilizing energy-based control, the system dynamically adjusts motion and force, responding to variability in device design, damage states, and environmental uncertainties.

and stored in a vector database. At inference time, the current camera image is used as a query. The system performs a cosine similarity search in the vector database to retrieve the most relevant image–text pair. The retrieved image is then concatenated side-by-side with the current camera image and added to the VLM prompt, along with the associated question–answer text. To summarize, the VLM prompt consists of

- the concatenated image (retrieved + current),
- the questions and answers associated with the RAG image,
- list of active workcell modules and their descriptions,
- list of detected e-waste objects and known symbolic relations,
- list of detected and known PDDL relations, and
- list of valid actions with arguments and brief textual descriptions.

The VLM is prompted to respond in JSON format with fields *reasoning*, *action*, and *action_input*. This allows for efficient output parsing. The *reasoning* field, generated using chain-of-thought prompting, helps interpret the VLM's decision-making. The *action* field specifies the name of the next action to be taken, while the *action_input* field provides the required arguments, typically including a robot or a tool and a target object.

The proposed prompts are not VLM-specific, but can be used with different models. In our experiments, we used different variations of the Qwen2.5-VL [15] and the GPT-4o [16] model.

B. Tactile skills and adaptation

Robotic disassembly of WEEE for the purpose of recycling demands advanced tactile manipulation skills, such as *levering*, *unplugging*, and *unscrew-driving*, capable of addressing variability in design, damage states, and environmental uncertainties at low-level control, as illustrated in Fig. 5. *Unified force-impedance control (UFIC)* [17] provides a robust framework to enhance robotic systems for these tasks by enabling adaptive, compliant manipulation tailored to the intricate demands of WEEE disassembly [18], [19]. This section outlines how these methods address specific challenges discussed in Section II.

WEEE recycling involves components with irregular geometries, different states of damage, and complex mechanical constraints. Traditional robotics, relying on static motion and force control policies, fails to adapt to such uncertainties. In our approach, robots dynamically adjust their stiffness and force based on real-time interaction feedback through stiffness-adaptive Unified Force-Impedance Control (UFIC). This approach relies on leveraging energy transfer between the robot and the environment and ensures safe and efficient manipulation even in cases of unpredictable constraints. It is particularly beneficial for tasks like battery removal, where rigid battery compartments pose significant risks of damage if an excessive force is applied. By enabling compliant behavior, UFIC ensures precise yet adaptable operations during disassembly.

Recycling tasks frequently involve environments with limited visual access or occlusions. Tactile exploration using UFIC with integrated visual feedback enables robots to identify and adapt to local constraints such as local curvature and surface irregularities, as we proposed in [20]. This capability is crucial for identifying battery compartments, which are often occluded and cannot be analyzed by visual perception. Additionally, virtual energy tanks preserve the system's stability during abrupt environmental changes, such as contact loss, which is significant for robots operating under complex control schemes while interacting with unstructured environments [17].

To manage the vast diversity of WEEE, our research emphasizes tactile skill learning through both data-driven and model-based approaches. The applied approaches leverage the inherent representation of tactile manipulation, which captures the force-motion relationships essential for performing adaptive tasks under varying conditions. By encoding the desired dynamic interaction between the robot and its environment into a phase-based representation, the system can identify and segment key stages of manipulation, such as establishing contact, tactile interaction, and terminating contact. This framework allows robots to maintain robust interaction by dynamically adjusting their behavior in response to uncertainties, such as misalignment between the tool and the piece or imprecision in positioning. This way the robot can ensure compliant yet precise control through impedance and force shaping, exploiting the exchanged energy between the robot and the environment.

Unlike static execution methods, this representation-driven approach incorporates real-time sensory feedback to adapt skill parameters dynamically. For example, if unexpected resistance arises while attempting to lever a cover, the robot can modulate its force application and motion trajectory in response [21], transitioning smoothly between manipulation phases. This ability reduces the likelihood of task failure and ensures robust tactile manipulation in unstructured and variable recycling scenarios.

By addressing the challenges of robotic disassembly with *adaptive tactile skills* and *UFIC*, our approach bridges the gap between automation capabilities and the demands of WEEE recycling.

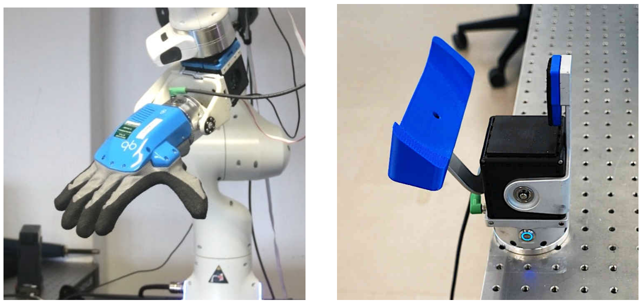
C. *Soft robotics*

Soft robotics offers an interesting approach to address challenges in robotic disassembly, especially in unstructured environments like e-waste disassembly. Unlike traditional rigid robots, soft systems are characterized by flexibility, adaptability, and resilience, making them ideal for handling fragile, irregularly shaped, or non-standardized objects. Inspired by biological systems, they leverage compliance, distributed actuation, and deformability to interact safely and effectively with diverse materials.

To address these challenges we focused our work on the development of novel, adaptive, and reconfigurable end-effectors based on the principles underlying the Pisa/IIT SoftHand [22], which uses motor synergies for adaptive grasping with reduced complexity. In this context, we both developed and explored the use of innovative soft robotics technologies (Fig. 6), for automated recycling, designed to enhance the system's adaptability in grasping and manipulation by incorporating resilience and flexibility to handle uncertainties. These innovations include two end-effectors, a clamping system, and a tool to improve manipulability. The designs and their application to the e-waste domain were inspired by the observation and analysis of common actions performed by humans during the disassembly of various e-waste objects (see Fig. 3): (i) power grasps for handling objects (e.g., e-waste housings) or operating disassembly tools, (ii) pinch grasps for small components (e.g., batteries), (iii) leveraging actions to separate snap-fitted parts, (iv) firm yet compliant holding to stabilize objects during disassembly tasks (e.g., maintaining stability on a support during a leveraging operation), and (v) manipulation of objects in constrained environments (e.g., retrieving items from boxes).

1) SoftHand 2: The SoftHand 2 [23] shown in Fig. 6a represents a significant improvement over the earlier design of the Pisa/IIT SoftHand, incorporating a synergistic dual-motor actuation that enables a large variety of grasp poses and in-hand manipulation capabilities [23]. The proposed dual-synergy approach allows the hand to adapt its shape dynamically, conforming to various object geometries (different sizes). It allows for seamless switching between precise pinching and power grasping, making the system highly adaptable. It can precisely handle small, fragile components like batteries – commonly found in electronic waste – while also enabling stable power grasps for larger objects, such as electronic waste housings, or for manipulating tools effectively (Fig. 7).

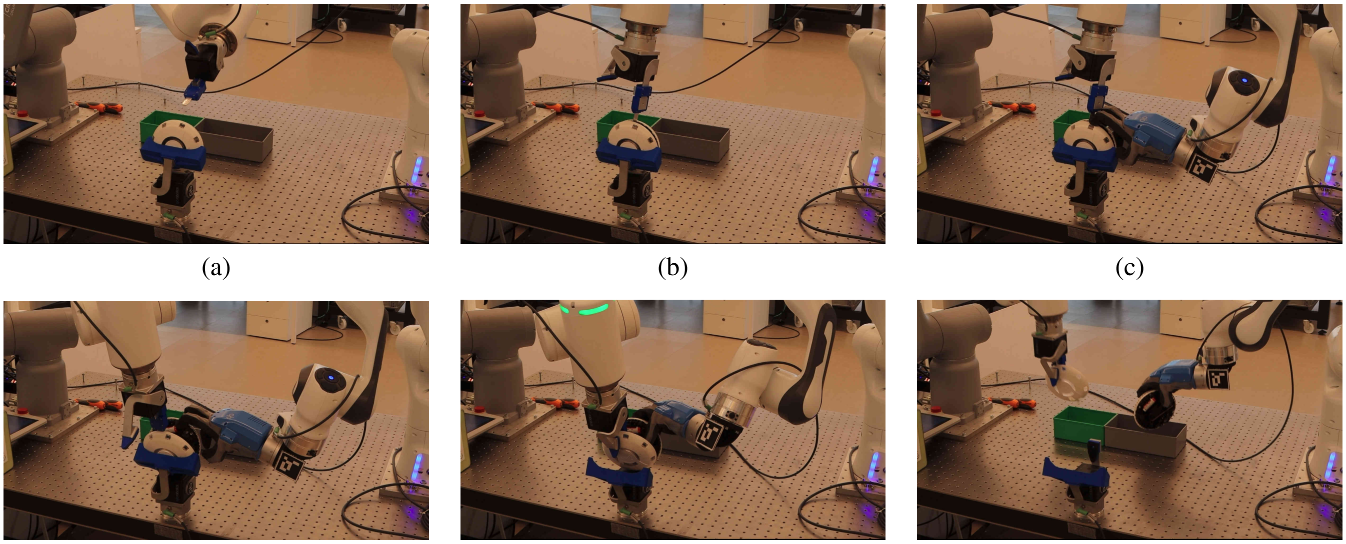
(a) SoftHand 2 (b) VS-Gripper



(c) SoftWrist (d) SoftClamp

Fig. 6. Soft robotics tools developed and adapted to the problem of disassembly of electronic waste.

2) VS-Gripper: The Variable Stiffness Gripper (VS-G) [24], Fig. 6b, features an agonistic-antagonistic elastic mechanism to modulate stiffness during the manipulation action. The system is based on a fixed finger, anchored to the housing of the gripper, and a movable finger, attached to the VS actuation system. The gripper's design allows for quick replacement of both fingers, enabling rapid adaptation to different tasks without extensive downtime. Thanks to this configuration, the gripper can be used to both execute levering actions (by exploiting the fixed finger) or grasp actions by controlling the actuation unit. Two primary modes are available –position control for setting specific angular positions of the gripper, and deflection control, which adjusts the stiffness based on the object's characteristics. This flexibility enables the gripper to handle a wide variety of materials and shapes. Additionally, it can be equipped with tactile sensors on its fingers to provide real-time feedback on force applications, contact points, and object stability. The proposed approach significantly improves performance in complex situations (e.g., handling slipping surfaces). For instance, the VS-G was successfully employed in the disassembly and extraction of electronic boards from heat-cost allocators (Fig. 9). The commercial version of the gripper is now available from qb robotics [24].



(a) (b) (c)

(d) (e) (f)

Fig. 7. Battery removal sequence for an exemplary smoke detector device. (a) The device is clamped in a soft vise for precise holding and positioning. (b) A custom tool on the SoftClaw disengages the tabs holding the covers, while the SoftHand2 stabilizes the rear cover using its compliant index finger. (c)-(d) One of the two manipulators pushes a tool to separate the front cover, aided by the SoftHand2 and the Soft Clamp adjusting its stiffness. (e) Once separated, the Soft Claw grasps the front cover, the SoftHand2 holds the rear cover, and the Soft Clamp releases the device. (f) Finally, the robotic arms place the parts into containers, with critical components undergoing further disassembly.

3) SoftWrist: The Soft Wrist, Fig. 6c, is an innovative one-DOF soft mechanism designed to enhance the adaptability and versatility of robotic end-effectors. It offers a 90° range of motion, achieved through a slider-crank mechanism combined with a rack-and-pinion system for precise and controlled movements. Traditional serial manipulator kinematics faces significant challenges in constrained environments [25], such as shelves, or boxes, especially when paired with anthropomorphic hands. In such configurations, aligning the end-effector with the required orientation for grasping is often difficult due to the bulkiness of the manipulator wrist kinematics. This problem is further compounded by singularities and the limited workspace of conventional robotic arms. Adding an additional degree of freedom (DOF) to the manipulator's wrist significantly improves its ability to overcome these constraints. Indeed, another degree of freedom reduces the overall system's bulk in the proximity of the object, which results in a better alignment of the grasping hand. In addition, we leverage the system's elasticity to compensate for inaccuracies, which makes the system more robust and reliable in complex scenarios. In our work, this system has been utilized in combination with the SoftHand 2 to effectively grasp objects contained in boxes provided to the system for disassembly tasks.

4) SoftClamp: The SoftClamp, Fig. 6d, was specifically engineered for non-destructive disassembly of glued, welded, or snap-fit components. It integrates a variable stiffness gripping mechanism, and two customizable jaws. One is fixed (fixed jaw), while the other is movable (movable jaw), which allows for adjustable clamping on the basis of the object shape. By mimicking human strategies (Fig. 3), the SoftClamp holding the object during the opening of a snap-fit housing plays a crucial role in managing force. It applies enough grip to stabilize the object securely while carefully modulating pressure (through the managing of the VS system) to avoid impeding the opening process (Fig. 7). By maintaining this delicate balance, the SoftClamp ensures the object is held firmly but flexibly, allowing the end-effector mounted on the manipulator to apply leverage or force effectively to release the snap-fit mechanism.

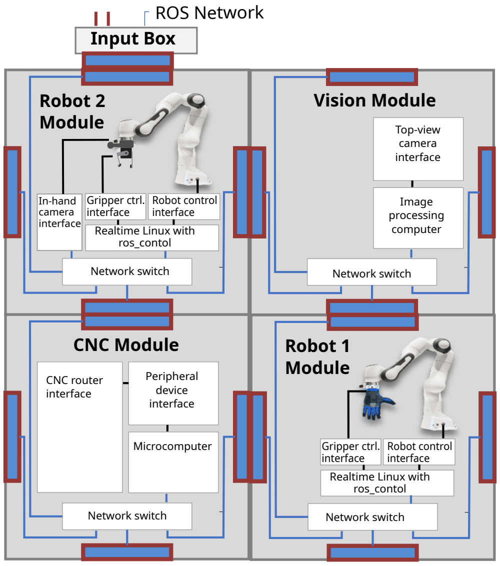
D. Reconfigurable robot cells

To accommodate a wide range of electronic devices for efficient battery removal, we followed a systematic approach towards the development of reconfigurable robotic workcells [26]. Traditional robotic workcells are designed to handle narrowly defined robot operations for predetermined product types, making it challenging to adapt to emerging products and dynamic market conditions. Addressing this limitation, our current architecture is based on modular, archetypical workcell units that can be easily rearranged and reconfigured into problem-specific layouts (see Fig. 8d). Standardized modules – such as cutters, vises, CNC milling stations, and inspection units – are mounted onto the base frame with innovative Plug & Produce connectors (Fig. 8b). These connectors ensure rapid mechanical, electrical, and pneumatic coupling, thus enabling the cell layout to be quickly adapted to a new set of devices without costly and time-consuming manual modifications.

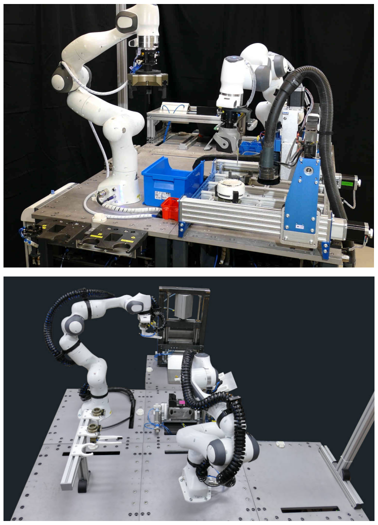
In addition to the hardware improvements, considerable attention has been devoted to software integration and process optimization. The entire workcell runs on a ROS-based architecture that allows seamless communication between robots, sensors, grippers, and other peripheral hardware. Each hardware element is controlled by dedicated microcomputers running containerized software modules, which simplifies deployment and maintenance (Fig. 8c). This approach also facilitates the integration of new components or the exchange of existing ones, as standardized software interfaces and communication

(a) Plug & Produce connector with pass-through units and alignment fixtures

(b) Archetypical module



(c) Software abstraction of hardware modularity



(d) Fully reconfigurable cell layout for different disassembly tasks

Fig. 8. Modular hardware and software architecture facilitates reconfiguration.

protocols remain unaffected by hardware-level changes. As a result, a reconfigurable workcell can accommodate devices of varying sizes, materials, and assembly complexities with minimal development overhead [27].

Enhancements have also extended to the flexibility and performance of the disassembly process. Instead of relying on custom-designed fixtures for each product type, general-purpose vises and adaptive grippers secure the workpieces. The system also benefits from integrated vision-based calibration and orientation detection. For example, an eye-in-hand camera mounted on a robot's end-effector allows the system to detect the position and orientation of a device, which is needed to dynamically adjust the processing sequence, and proceed with disassembly steps that remove various layers of the product to reach the embedded battery. In devices like HCAs, straight-line cuts suffice to free the battery, while more complex devices, such as smoke detectors, may require multiple precise milling steps. The introduction of CNC machining into the cell further increases versatility, as cutting paths can be adapted to the product geometry, and vacuum grippers can hold any detached parts to prevent uncontrolled debris from affecting the cutting tool. The resulting process significantly decreases the amount of manual intervention and allows smooth transitions between different device families.

An important element supporting these capabilities is the introduction of advanced optimization algorithms to compute optimal workcell layouts for disassembly [28], [29]. These algorithms rely on parametric models of the cell layout, constraints, and evaluation criteria, such as throughput, energy consumption, and ergonomic considerations. By systematically examining candidate cell configurations, an optimization algorithm determines suitable placements of hardware modules, ensuring that all components remain accessible within the robot's dexterous workspace. Simultaneously, it minimizes collision risks and avoid interference with other modules. The user can also incorporate task-specific constraints such as ensuring that a camera-equipped robot has a clear line of sight to the device or that a cutting operation is performed from a particular angle. By automatically producing optimized layout configurations, the cell setup time is reduced, and recurring manual adjustments are eliminated.

IV. EVALUATION

Extensive laboratory testing under realistic conditions has confirmed that the integrated approach – combining modular and soft hardware, flexible software architectures, advanced sensing, tactile skills, and optimization algorithms – substantially improves both the adaptability and efficiency of the workcell. Device families with markedly different layouts, assembly materials, and component positions can be processed without the need for extensive mechanical redesign or the creation of product-specific fixtures. This level of adaptability leads to greater material throughput, thus enhancing the overall operational performance.

The performance of the robotic workcell was assessed across multiple dimensions, with particular focus on the system's ability to handle various devices, adapt to the forces involved in disassembly operations, and accurately recognize and execute required actions.

A. *Object handling*

A critical factor in automated electronic waste disassembly is the range and variability of devices the system can reliably process. These devices differ significantly in size, shape, and internal architecture, necessitating adaptable handling strategies.

We evaluated the grasping and clamping performance of diverse end-effectors for adaptive grasping (SoftHand Research,

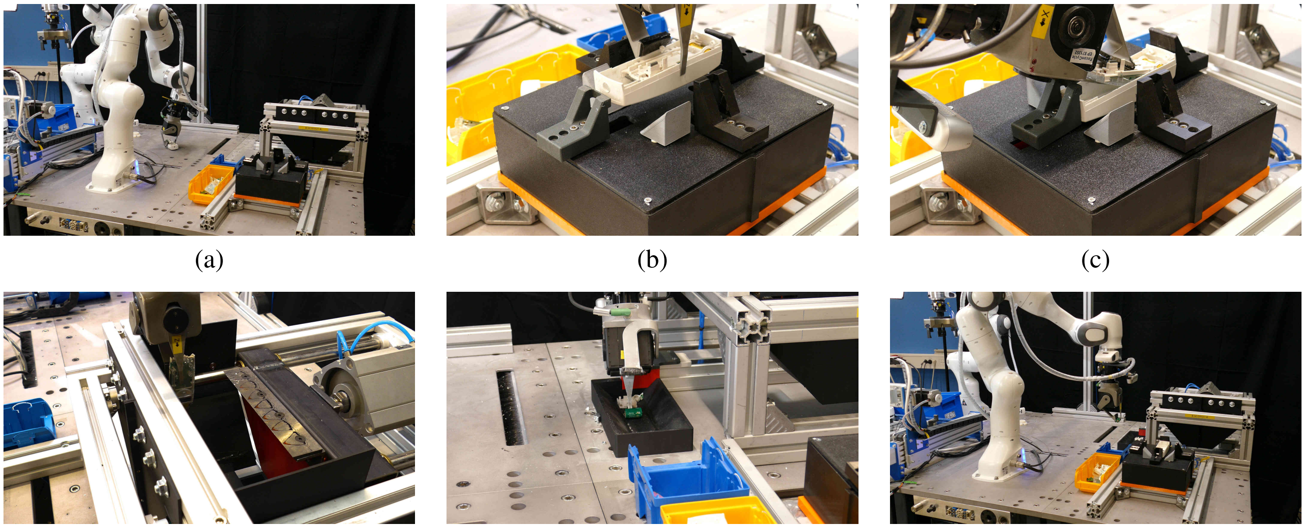

(a) (b) (c) (d) (e) (f)

Fig. 9. Automated battery removal sequence from an exemplary HCA device. (a) Device pose and class are determined by the vision system and picked up by a VS gripper. (b) The device is then transferred to a vice. (c) The device is securely clamped in the vice to provide a firm hold during the adaptive PCB levering process. (d) A cutting module is used to cut the bond holding the battery to the PCB. (e-f) The electronic board and battery are then transported separately to their designated bins.

SoftHand 2 and VS-Gripper) and dedicated pneumatic vises for workpiece holding (a vise with two pairs of jaws for rectangular-shaped objects and a three-finger vise for cylindrical objects). Rectangular-shaped objects (2 HCAs and their internals) had dimensions ranging from 70–120 mm in length, 35–40 mm in width, and 20–30 mm in thickness. Cylindrical objects (3 SDs and 2 batteries types) included batteries with a diameter of 15 mm and smoke detectors with diameters of 95 mm and 130 mm, and heights between 25–30 mm. For the grasping evaluation, pick-and-place loops were conducted, with each object being grasped 50 times. The end-effector approached the objects normal to the workplane surface. No vision system was used, so the objects were consistently placed in the same location but oriented randomly to simulate variability in placement. Success was defined as a firm grasp where the object would not fall during handling. In addition, 50 trials were conducted for each object, where a correctly grasped object was dropped into a fully opened vise. The pneumatic jaws were closed after the placement. Success was defined as the device securely clamping the object, allowing follow-up operations.

Object shape	SoftHand Research	SoftHand 2	VS-Gripper
rectangular	97.3%	96.9%	90.6%
cylindrical	81%	90%	80%

TABLE I
RELIABILITY OF GRASPING OF OBJECTS OF DIFFERENT SIZES AND SHAPES AT DIFFERENT ORIENTATIONS.

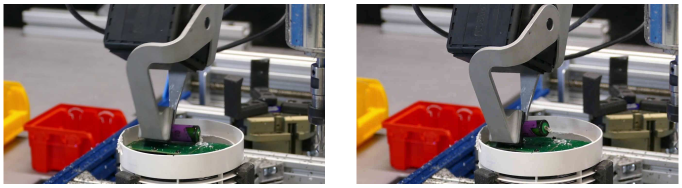
As shown in Table I, grasping success rates varied across different end-effectors, guiding the selection of the most suitable end-effector for specific object operations. The clamping mechanism achieved a success rate exceeding 98.5%, demonstrating robust performance across diverse tasks. This level of reliability, combined with the system's hardware and software modularity, confirms its scalability to handle a wide range of diverse electronic products.

B. *Force control*

Force control and reaction management during disassembly operations present a distinct set of challenges, primarily due to the physical variability and unknown states of damage of devices to be dismantled. Our system addressed these issues by integrating Unified Force-Impedance Control (UFIC) [17], which enables dynamic modulation of stiffness and force in response to real-time interaction feedback. This approach allowed the robot to maintain safe, compliant behavior even in situations requiring the application of significant force, such as levering PCBs or detaching fixed-mount batteries from the PCBs.

There are various methods for detaching such batteries. The contacts can be broken using a rocking motion pattern combined with pulling or levering, milling away the contacts, or cutting the wires. We evaluated a smoke detector type where the battery contacts were dislodged using a rocking motion combined with pulling, as shown in Fig. 3b. We assumed that the smoke detector internals were securely clamped in a fixture and the battery was correctly located for the VS gripper to grasp it, as shown in Fig. 10. While holding the battery, the robot performed a rocking motion to apply force on the contacts, pulling them apart. The process was deemed successful when the counter-force dropped. The maximum duration for the rocking process was set to 25 seconds. If counter force was still detected after this time, the process was considered a failure.

Out of 20 battery removal attempts, 18 were successful. The failures occurred during the contact-handling step. In one case, the contacts remained attached to the PCB, causing the entire PCB to be dislodged from the smoke detector case. In the second failure, the extraction process immediately broke



(a) (b)

Fig. 10. Battery removal based on rocking motion pattern and pulling

one of the two contacts, causing the remaining part to rotate around the intact contact instead of breaking it. This contact was not removed within the maximum process duration, and these cases were left for manual disassembly.

C. Action prediction and monitoring

To support decision-making beyond the physical execution layer, the proposed system incorporates a Vision-Language Model (VLM) framework designed for both action prediction and monitoring. This framework combines visual inputs from the environment with natural language instructions to identify the most suitable disassembly actions at each step of the process. Additionally, it provides feedback on whether the actions carried out by the robot were successful, closing the loop between perception, reasoning, and execution.

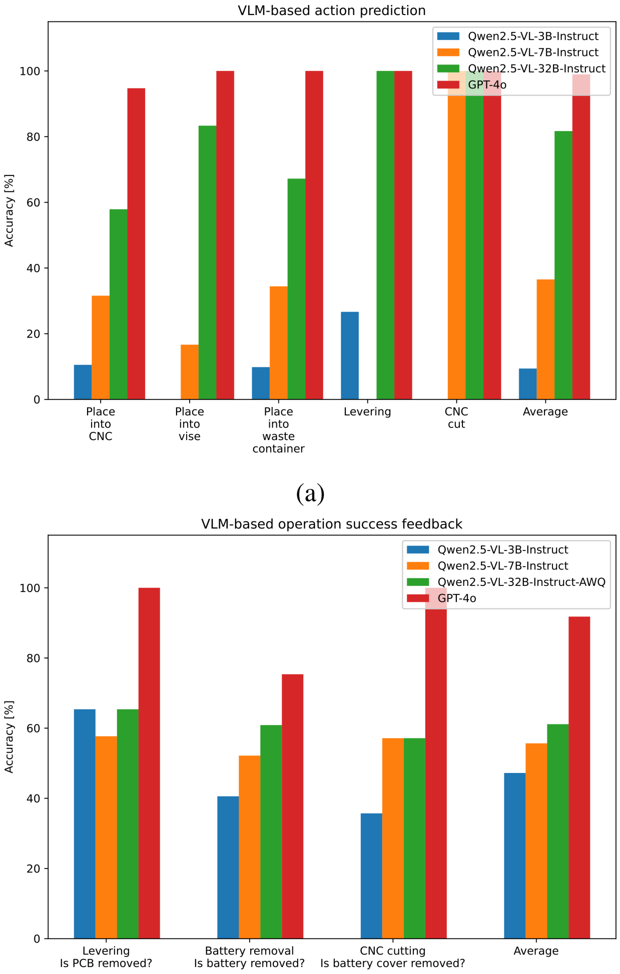
To evaluate the effectiveness of this component, several models were tested on two core tasks: predicting the next appropriate disassembly action and assessing the outcome of executed operations. These included three open-source models, Qwen2.5-VL-3B-Instruct, Qwen2.5-VL-7B-Instruct, and Qwen2.5-VL-32B-Instruct-AWQ, as well as a proprietary model, GPT-4o. Each was assessed for its ability to interpret multimodal inputs and contribute to reliable and adaptive system behavior.

For the next action prediction task, prompts were generated as described in Section III-A1 Five different actions were selected for evaluation. The testing set comprised 150 images depicting different steps of the disassembly process of 6 different devices (4 smoke detector types and 2 heat cost allocator types). The best-performing model succeeded in correctly predicting the next action in 98 % of the cases (see Fig. 11a).

For the action success feedback task, the models were provided with a reference image showing a successful operation, the query image showing the actual current state, as well as a description of the expected outcome (e.g. “the PCB should have been removed”). The reference images were retrieved using the RAG system. In this case, the best performing model achieved a 84 % accuracy in correctly predicting the success of the executed action (see Fig. 11b).

V. DESIGN FOR DISASSEMBLY

In our examination of Waste Electrical and Electronic Equipment (WEEE), we found that many devices require destructive disassembly methods, limiting their potential for reuse and repair. Such approaches not only hinder circularity but also increase the complexity and cost of recycling and remanufacturing efforts [30].



(a)

(b)

Fig. 11. VLM-based action prediction evaluation (a) and success feedback evaluation (b)

While advancements in robotics and computer vision have helped address some challenges, these innovations must be complemented by fundamentally new design strategies that anticipate diverse product conditions and prioritize ease of disassembly. Historically, much attention has been given to advancing automated assembly technologies; however, designing devices to facilitate efficient manual and automated disassembly is equally critical [30].

The concept of Design for Disassembly (DfD) is increasingly recognized as a key enabler of sustainable and circular economic practices. Practical implementation of DfD incorporates features such as reversible joints and standardized fasteners, reducing reliance on destructive methods like cutting. Instead, it emphasizes non-destructive techniques such as unclipping, levering, or unscrewing, which help preserve the integrity of components and materials for subsequent reuse or recycling.

Despite its clear benefits, widespread adoption of DfD faces several challenges. There are two primary barriers to effective product disassembly, particularly in re-manufacturing contexts.

Firstly, initial design choices – such as the use of irreversible fasteners or permanent bonding agents – often preclude non-destructive disassembly, which leads to component damage and reduced reusability. Secondly, the variability in the design and condition of used products complicates the development of universal disassembly solutions. Devices returned for remanufacturing may exhibit differing levels of wear and tear, requiring adaptable robotic systems capable of handling unpredictable scenarios.

In this paper we tackled the second issue by incorporating advanced tactile skills, flexible hardware modules and soft robotics, and robust machine-learning strategies – particularly through the use of large vision-language models – to adapt to a wide range of product conditions in real time. These advances allow for efficient disassembly despite differences in device design, integrity or inconsistent positioning of components. However, we did not focus on altering device design itself; our solutions rather underscore the ongoing need for upstream design improvements. Implementing design features that facilitate non-destructive disassembly – such as standardized fasteners or modular components – would further enhance the effectiveness of robotic systems by reducing complexity and lowering the likelihood of irreparable damage during disassembly. Promoting the use of common fasteners and assembly techniques could simplify both manufacturing and disassembly, making automated and manual processes more efficient.

VI. CONCLUSION

This paper introduced an advanced robotic framework for automating battery removal in WEEE recycling, addressing key challenges such as diverse device designs, complex disassembly requirements, and varying damage conditions.

One of the key contributions is the integration of Vision-Language Models (VLMs) with Retrieval-Augmented Generation (RAG) to create adaptive disassembly strategies within the processing loop. This approach moves beyond traditional rule-based systems, offering greater flexibility and scalability without the need for extensive pre-programmed instructions. The use of a PDDL-based environment description further ensures logical consistency in disassembly sequences, reducing errors and improving reliability.

Another major innovation is the development of a robotic system that combines high-frequency tactile feedback, force-impedance control, and soft robotics. Adaptive end-effectors, including the SoftHand 2, VS-Gripper, SoftClamp, and SoftWrist, enhance dexterity and allow safe and precise battery removal even from fragile or tightly integrated devices. This approach minimizes damage and reduces risks such as battery punctures and fire hazards.

Additionally, the introduction of a modular and reconfigurable robotic workcell architecture allows for rapid adaptation to various device types without major hardware or software modifications, making it a practical solution for large-scale recycling operations.

However, several limitations remain. While VLMs offer flexible reasoning, they occasionally suggest infeasible actions, particularly when visual ambiguity is high or retrieved RAG content is weakly aligned. These issues can be mitigated in part by symbolic action constraints and success-checking routines, but they highlight the need for continued refinement. Another challenge is motion adaptation, which must ensure that actions such as levering can be executed appropriately across different device geometries; this generally works but can require reparametrization for certain designs. These observations are grounded in extensive experimental validation and highlight both the technological progress achieved and the remaining practical challenges encountered during real-world deployments.

We have also found that the system's adaptability comes at a cost: execution speed is typically lower compared to fixed-task automation, and maintaining real-time responsiveness poses challenges when scaling to high-throughput environments. Furthermore, long-term durability of soft robotic components requires further validation in industrial settings to ensure operational reliability.

By systematically integrating these technological advancements, recycling cells are moving closer to realizing a generalized disassembly platform capable of handling the continuously evolving landscape of electronic devices. Although a fully automated solution for all device types has not yet been achieved, the system can already process a significant range of products within specific device families. This progress strengthens the viability of automated recycling operations, where diversity in product design is the norm rather than the exception. As electronic products continue to diversify, reconfigurable, adaptive, and easily optimizable robotic systems represent a robust, future-oriented strategy for sustainable e-waste handling and resource recovery.

Beyond technical innovations, this research underscores the critical role of design-for-disassembly (DfD) principles in improving the recyclability of electronic devices. While robotics can greatly enhance the efficiency of disassembly processes, incorporating standardized fasteners and reversible joints during product design could further streamline recycling. Combining advances in robotics with better product design is essential for achieving sustainable and economically viable e-waste management.

In summary, this work advances robotic disassembly for recycling and lays a foundation for scalable, adaptable recycling solutions. Future research will focus on improving robustness under visual uncertainty, enhancing motion generalization, broadening the range of applicable devices, and validating the system in industrial-scale recycling environments to increase material recovery and promote sustainability.

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