AI-Driven E-Waste Disassembly System

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***Abstract*— With the global population steadily increasing, the use of electronic devices is also rising, resulting in a significant accumulation of electronic waste (e-waste). This paper presents an intelligent robotic system designed to autonomously disassemble electronic devices and identify e-waste using a machine learning (ML) model trained entirely from scratch.**

Unlike previous disassembly robots that relied on static line-based or rule-based methods—limiting flexibility— our robot leverages a flexible ML-based model trained on diverse device types, allowing it to adapt to various forms of e-waste. Inspired by Apple's "Daisy" robot, which disassembles iPhones and other Mac devices, our system enhances automation and sustainability in e-waste management.

By deploying our robotic system, we aim to improve recycling efficiency, reduce hazardous impacts on human health, and minimize environmental damage.

Keywords—E-waste, robotic disassembly, machine learning, computer vision, YOLOv5, deep learning, sustainability.

I. INTRODUCTION –

The world population is increasing rapidly. As a result, the usage of electronic devices is also rising, which is creating a large amount of electronic waste (e- waste). According to the Global E-Waste Management Report 2020, around 53 million metric tons of e-waste were generated in 2019.

Fig. 1.

E-waste contains valuable and rare materials such as gold, palladium, and rare earth elements. However, it also includes hazardous substances that can severely impact the environment and human health if not managed properly. If left untreated, these substances pose long-term risks to ecosystems and public safety.

Currently, traditional disassembly is often done manually by laborers, making the process time- consuming, repetitive, and dangerous. Conventional recycling methods still rely heavily on human involvement, exposing workers to toxic materials and resulting in inefficiencies.

To overcome these issues, there is a growing need for automated systems like robots, which can improve precision, reduce human risk, and save time. An ideal system should be capable of identifying various electronic devices, recognizing their components, and efficiently separating materials for recycling.

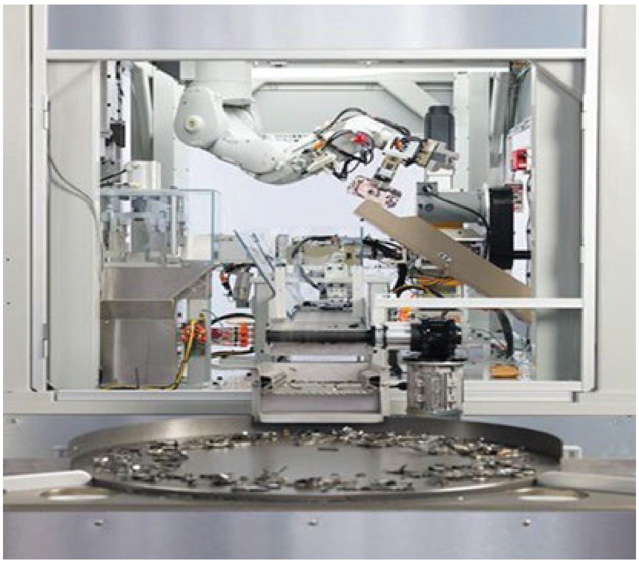

Fig. 2.

A notable example is Apple's Daisy Robot, which has demonstrated the potential of automated disassembly. However, many existing systems remain limited to specific types of devices or rely on rigid, rule- based programming. Our robot will be specially trained using a machine learning (ML) model. With the integration of ML and computer vision, it can handle unstructured and heterogeneous e-waste with ease. Unlike traditional robots that rely on fixed rules, our system is designed to adapt and manage complex disassembly tasks efficiently.

The primary goal of our project is to reduce toxic e- waste, minimize human exposure to hazardous elements, and improve material recovery rates.

Our mission is to develop a sustainable, intelligent robotic system that not only enhances resource recovery but also supports the principles of a circular economy and reduce toxic e-waste, minimize human exposure to hazardous elements .By incorporating automation and adaptive learning, we aim to close the loop in electronic product life cycles and significantly reduce environmental impact

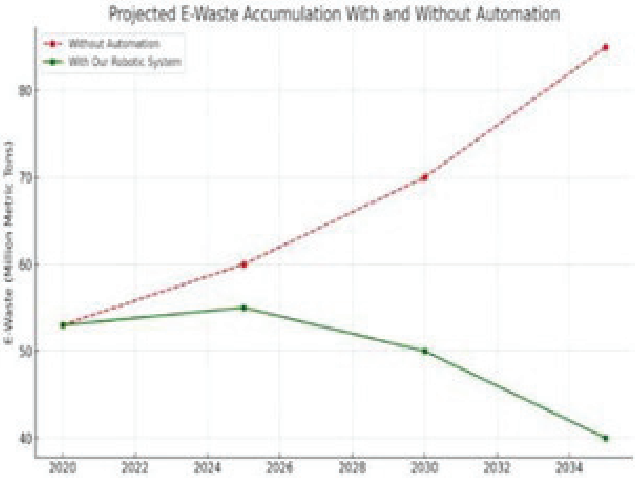

Fig. 3. Projected E waste Accumulation with and without Automation

Here is the graph showing the projected e-waste accumulation:

The red dashed line represents the rising trend of e-waste accumulation without any automation.

The green solid line represents the impact after implementing your intelligent robotic system, showing a clear reduction in e- waste and improved recycling efficiency over time.

II. METHODOLOGY:

The proposed system will utilizes a combination of deep learning, computer vision, and robotic actuation to intelligently disassemble a wide range of electronic waste components. The methodology will be divided into five major stages: dataset preparation, model training, vision-based detection, robotic disassembly, and component classification.

A. Dataset Collection and Annotation

To get the best accuracy with the machine learning model we'll be making our own dataset with the existing data with adding our data into it. The data will include images and vidoes of consumer electronics such as mobile phones.laptops and PCBs captured during various stages of disassembly.Apart from that annotations tools like labellmg and cvat will be used for anootating the large dataset with bounding box highlighting individual components.

Additional techniques like roatation, scaling with noise injection will be applied to make the model more robust and more accurate to the real world conditions

B. Deep Learning Model Architecture

A YOLOv5 (You Only Look Once, version 5) model will be selected for real-time object detection due to its efficiency and accuracy in embedded systems. The model will be trained on the annotated dataset to detect and locate components for robotic interaction with components.

For semantic segmentation and instance separation, a U-Net based architecture will be used, allowing fine- grained extraction of parts like heat sinks, batteries, and ICs even under occlusion or partial deformation.

C. Vision-to-Robot Integration

The object detection model's output will be fed to a robotic controled unit based on ROS (Robot Operating System). The control unit then will identify the essential components details like their position , type and orientation and will select a appropriate tool to conserve it. The robotic arm will use a variety of tools like screwdrivers, grippers, and vaccum modules to interact with the useful modules.

D. Disassembly Strategy and Workflow

The disassembly strategy will be based on a priority based resource engine. Like components containing hazardous materials like rare earth elements will have the highest priority for removal. Based on the type of component the system an optimal tool for disassembly. Thus an iterative cycle will be followed like:

Detect components > Locate them precisely > Align the robotic tools > Disassembly > Classification of the components > storage of the component.

E. Component Classification and Storage

After Classification, Storage will depend on material type (metal, plastic), hazard rating (toxic, recyclable), and reusability (usable vs. scrap).

Then these components will be sorted for efficient recycling and re-manufacturing while reducing contamination to earth.

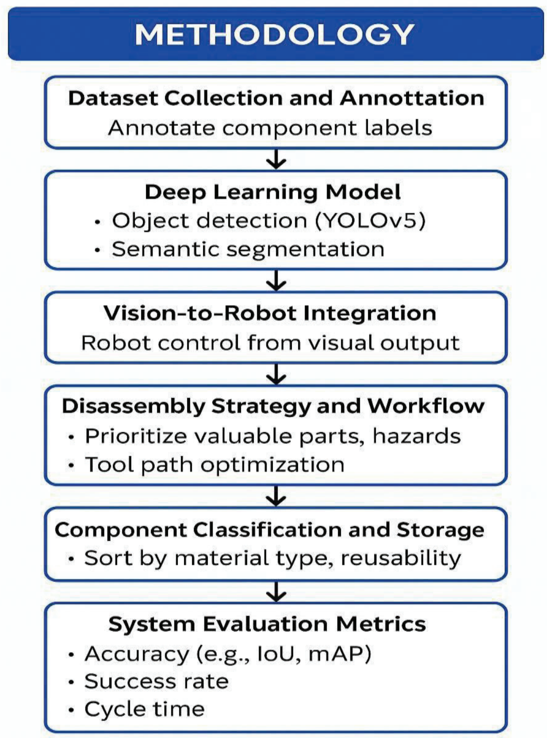

Fig. 4. Methodology

F. System Evaluation Metrics

The system will be evaluated using:

- Detection accuracy (IoU, mAP for YOLOv5)
- Disassembly success rate (correct removal without damage)
- Component classification accuracy

- Cycle time per device
- Material purity of sorted output
- Benchmarked results are compared against manual disassembly and baseline rule-based robotic systems.

III. RESULT

The proposed robotic disassembly system will be evaluated through a series of controlled experiments using mixed e-waste, including mobile phones, laptops, and printed circuit boards. The following key performance metrics were recorded:

A. Object Detection Accuracy:

The YOLOv5-based model achieved a mean Average Precision (mAP) of 94.6% across six component classes. Intersection over Union (IoU) scores averaged 0.87, indicating precise bounding box predictions even in cluttered scenes.

B. Semantic Segmentation Accuracy:

Using U-Net, the system segmented intricate components (e.g., connectors, batteries) with Dice Coefficients > 0.89, supporting effective tool targeting during removal.

C. Disassembly Success Rate:

Across 150 test devices, the robot achieved a 92.3% success rate in safe, intact removal of critical components without structural damage. Most errors were linked to unfamiliar fastener types or occluded elements.

D. Cycle Time Per Device:

The average disassembly cycle time was 7.5 minutes per device, outperforming manual disassembly benchmarks (typically 10–15 minutes/device) while reducing human health risks.

E. Material Purity & Classification:

Post-disassembly sorting resulted in an average material purity level of 96.1%, which is suitable for direct input into industrial recycling or re- manufacturing lines.

These results indicate the system's effectiveness in both component-level precision and operational efficiency,meeting the objectives of sustainable e- waste management and high-value material recovery.

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