Edge-AI Driven Automation for Scalable E-Waste Recycling

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1. Introduction

Electronic waste (e-waste) is a rapidly growing waste stream, and efficient disassembly is essential for material recovery and safe recycling. A key bottleneck in current recycling workflows is the manual removal of screws from device housings. This process is labour-intensive, repetitive, and difficult to scale, motivating the development of automated solutions.

Automating screw removal is challenging due to variations in fastener geometry, surface finish, lighting conditions, and device layouts. While industrial robotic systems have demonstrated technical feasibility, their high cost, calibration complexity, and reliance on proprietary hardware limit practical deployment in low-margin recycling environments.

This research presents a low-cost, vision-guided robotic system for automated screw extraction from laptop back panels. The system combines a Cartesian CNC-style gantry with edge-based computer vision to localise screws and perform planar positioning with sufficient precision for mechanical engagement. By leveraging low-cost hardware, the system aims to demonstrate a practical and scalable approach to automating a critical disassembly step in e-waste processing.

2. Related work

Prior work on automated disassembly largely employs either articulated robotic arms or high-precision Cartesian gantries. While these systems demonstrate technical feasibility, they typically rely on expensive hardware, complex calibration procedures, and proprietary control stacks, limiting practical deployment in low-margin e-waste recycling environments [1]–[3]. This motivates the development of a low-cost, modular alternative.

The system developed in this work adopts a Cartesian gantry architecture but emphasises accessibility and modularity by utilising commodity hardware and resource-constrained computer vision. This approach seeks to retain the speed and repeatability of planar systems while reducing cost and deployment complexity, thereby addressing practical constraints in e-waste recycling. Inherent limitations of the system will subsequently be discussed.

3. Methodology

The prototype is built upon a distributed control architecture comprising two Arduino UNO microcontrollers and a Raspberry Pi 4B (4GB RAM). The system integrates NEMA 17 stepper motors for planar motion, an N20 DC motor for rotational torque, and an MG90S servo motor for vertical actuation. The primary Arduino UNO, equipped with a CNC shield, manages the X-Y gantry motion via belt-driven stepper motors. A secondary Arduino UNO is dedicated to the tool head, directly controlling the MG90S servo to lift or lower the mechanism and the N20 motor for unscrewing operations.

To support the training of a robust YOLOv11n model, a diverse dataset was compiled. Primary data collection involved capturing high-resolution RGB images of laptop frames under varying lighting conditions, background textures, and object arrangements. Screws were captured in multiple orientations to simulate real-world operational variability. In total, 382 raw images of laptops were manually collected. To increase the manual dataset and reduce annotation overhead, 500 synthetic images were generated. Background textures of laptop panels were sourced from web search engines. A Python script was then used to superimpose screw images at random coordinates onto these backgrounds or onto generated dark gradients, matching most modern laptops.

This primary dataset was further supplemented with 90 labelled images from the Cross-Recessed Screws Deep Learning Dataset, released by Brogan et al. [4] for robotic disassembly applications.

The models were trained on a Google Colab Pro instance with an NVIDIA A100 GPU (80GB VRAM) with an image size of 640x640 (with the exception of YOLOv11x), which is the maximum image size for exporting to the IMX500 vision sensor.

After training, the model was exported to the IMX500 format, which is designed to make use of the Sony IMX500 Intelligent Vision Sensor in the Raspberry Pi AI Camera. This uses minimal power while delivering fast performance for neural networks such as the trained screw detection model. The model was exported with post-training quantisation (PTQ).

4. Results

The YOLOv11 family consistently demonstrated strong performance across all configurations. Both YOLOv11n and YOLOv11s achieved high mAP@50 values (≥ 0.967) with precision and recall remaining above 0.92 in all cases.

After evaluating the performance of the models, we used YOLOv11n trained for 300 epochs as the final model. Despite its lightweight architecture, it reached mAP50 values comparable to larger variants, with strong precision and recall, making it a favourable tradeoff between accuracy and efficiency. This made it ideal for inference on the Raspberry Pi 4B.

To validate the integrated system's mechanical reliability, we conducted four distinct trial runs across three different laptop models: a Dell Inspiron 5490, a Lenovo G500, and an Acer Chromebook 311. One device was subjected to two separate trials to assess repeatability.

The vision model successfully localised 25 potential screw positions across the four trials. Of these 25 attempted extractions:

- 17 attempts resulted in successful engagement and removal, yielding a mechanical success rate of 68%.
- 8 attempts failed due to positioning errors exceeding the system's tolerance threshold of 3 mm.

5. Conclusion

This project demonstrates the feasibility of a low-cost, vision-guided robotic system for automated screw extraction in e-waste recycling. By integrating a Cartesian gantry with edge-based object detection, the system achieved reliable planar positioning and autonomous engagement of fasteners, validating the core concept of modular, scalable disassembly automation.

While the prototype achieved a mechanical success rate of 68%, several limitations were identified. The use of a planar gantry restricts operation to flat surfaces, static camera-to-frame calibration introduces drift under mechanical vibration, and the open-loop end-effector lacks torque feedback for robust engagement with damaged or variably seated screws. Additionally, detection performance remains sensitive to visual conditions and background complexity, constraining generalisation.

Future iterations will incorporate closed-loop motor control, torque sensing, and an eye-in-hand perception architecture to improve positional accuracy and robustness. An automated tool-changing mechanism and expanded training datasets will further extend the system’s applicability to full-device disassembly. Overall, this work establishes a foundation for accessible, scalable automation in e-waste processing, bridging the gap between manual labour and high-cost industrial systems.

References

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