TRANSFORMING MATERIALS RECOVERY FACILITY USING A.I.-DRIVEN SMART MODULAR SYSTEM

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Abstract: Efficient resource recovery is crucial for supporting manufacturing industries, reducing waste, lowering material costs, and strengthening the economy. This paper presents a novel artificial intelligence (AI)-driven approach to recovering valuable materials from municipal solid waste (MSW) including consumer batteries, and other critical materials in the form of e-scrap using low-cost, custom-built high-speed robotic actuators. By integrating advanced image-based AI sorting algorithms with 2-3 axis actuators, this approach enables high throughput, precise and scalable recovery of materials, driving the transformation of materials recovery facilities (MRFs) and supporting a more circular economy. AI models were trained on diverse image datasets capturing visual patterns and features across various material types. A unique aspect of the system is its efficiency: a single image is captured for AI analysis, enabling the identification and classification of all targeted materials, including plastics, metals, paper, fabric, glass, consumer batteries (Li, Ni, Alkaline), and critical material in form of e-scrap. These can be recovered in one pass relying solely on image data for classification and sorting. The robotic actuators are designed for high-speed and cost-effective operations with multiple end-effectors specific to each of the above materials, enabling efficient handling and separation of materials at industrial scales. This modular system drives significant improvements in recovery rates and material purity while maintaining low operational costs, and can be easily retrofitted in current MRFs. It transforms MRFs by enabling the recovery of a wide variety of materials and can be extended to refine separation further within each category. This patented one-pass recovery approach enhances processing speed and throughput, facilitating the recovery of high-quality secondary materials while reducing reliance on virgin resources, minimizing greenhouse gas emissions, and aligning with global sustainability and decarbonization goals. Future work will focus on expanding the system to industrial-level demonstrations by optimizing both algorithms and hardware for greater efficiency and scalability. Additionally, the system will be enhanced to accommodate more material categories and subcategories, enabling refined separation and broader applicability. By addressing economic and technological challenges, this research provides a scalable and impactful solution for resource recovery, contributing to a resilient and sustainable manufacturing economy. The integration of AI and robotics demonstrates significant potential to revolutionize MRFs and advance the circular economy through efficient, cost-effective, and precise material separation. This project is funded in part by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under award number DE-EE0011361.

Introduction and Motivation

The United States faces a significant challenge in resource recovery and waste management, with approximately 146.1 million tons of waste being landfilled in 2018 alone [1,2]. This represents a staggering loss of embedded energy, estimated at ~2×10^{18} Joules (~2 quads), much of which consists of recyclable materials including paper (12%), plastics (18%), textiles, metals, glass, and critical materials that could be reintegrated into the manufacturing economy [2]. Current manual sorting methods at Materials Recovery Facilities (MRFs) are inefficient, unreliable, and cost-prohibitive, resulting in valuable resources being lost to landfills, with the U.S. spending approximately $200 billion annually on solid waste management and lost energy resources [3]. Fig 1 shows various types and quantities of material that were landfilled in 2018.

This inefficiency in resource recovery has far-reaching implications for manufacturing industries, environmental sustainability, and economic resilience. The inability to effectively recover and process these materials increases

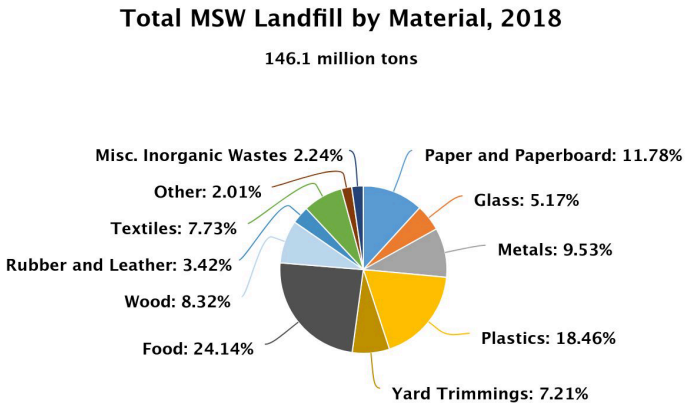


Figure 1: *Types and quantities of recyclable material in MSW that goes to landfills.*

dependence on foreign imports of raw materials, elevates manufacturing costs, and contributes to environmental degradation. This challenge is particularly acute given the declining recycling rate from 35% in 2017 to 32% in 2018 [1], exacerbated by global market disruptions such as China's National Sword campaign [3].

To address these challenges, this paper presents a novel artificial intelligence (AI)-driven approach for efficient resource recovery from municipal solid waste (MSW). The proposed system integrates advanced image-based AI sorting algorithms with custom-built high-speed robotic actuators, enabling high-throughput, precise, and scalable material recovery. This innovation represents a significant advancement over traditional sorting methods, offering a modular solution that can be retrofitted into existing MRFs without extensive infrastructure modifications.

The system's unique capability lies in its one-pass recovery approach, where a single image capture enables the identification and classification of multiple material types simultaneously. This efficiency is achieved through sophisticated AI models trained on diverse image datasets, coupled with specialized end-effectors designed for handling various materials including plastics, metals, paper, fabric, glass, consumer batteries, and e-scrap. The integration of these technologies not only enhances recovery rates and material purity but also maintains operational cost-effectiveness, addressing both economic and environmental imperatives in waste management.

By enabling more efficient resource recovery, this technology aligns with broader sustainability goals, including reduced greenhouse gas emissions, decreased reliance on virgin resources, and advancement toward a more circular economy. With global waste generation projected to reach 3.4 billion metric tons by 2050 [3], and the U.S. Municipal Solid Waste Management Market expected to surpass $25 billion by 2024 [3], the system's ability to process multiple material streams simultaneously while maintaining high accuracy represents a significant step forward in transforming waste management infrastructure and supporting sustainable manufacturing practices.

Current State of the Technology Industry Uses

The current state of material recovery in the waste management industry predominantly relies on manual labor and traditional sorting methods, which have proven to be both inefficient and unreliable [1]. Material Recovery Facilities (MRFs) face significant challenges in processing the increasing volume and complexity of waste streams, particularly in handling mixed materials and identifying valuable components within municipal solid waste (MSW). In existing facilities, manual sorting remains the primary method of material separation, where workers visually identify and manually separate materials on conveyor belts, as shown in Fig 2 [18]. This approach inherently limits throughput capabilities while introducing inconsistencies in sorting accuracy. The reliance on manual labor also presents substantial operational costs and worker safety concerns, ultimately affecting the quality of recovered materials [2].

Figure 2: *Workers at an MRF, sorting waste materials and removing contaminants.*

The mechanical separation technologies currently employed in the industry consist primarily of magnetic separators for ferrous metals, eddy current separators for non-ferrous metals, trommel screens for size-based separation, and air classification

systems for light materials. While these technologies have served as the backbone of material recovery operations, they face considerable limitations in meeting modern recycling demands [3]. A significant constraint in current automated sorting systems lies in their binary separation capability, where systems can only perform accept/reject decisions for a single material type. This limitation necessitates multiple processing passes to achieve comprehensive sorting, substantially increasing operational costs and processing time. Furthermore, existing systems demonstrate limited recognition capabilities, particularly struggling to differentiate between similar materials or identify specific subcategories within material groups [4].

Some facilities have integrated 4- or 5-axis robotic systems to address automation, but these are typically limited by slower pick rates, high infrastructure costs, and reduced adaptability to diverse material types [9][10]. The pick rate of such systems is generally estimated at 40–60 picks per minute based on vendor specifications, which is insufficient to match the material processing rates of medium-sized MRFs, typically around 20–30 tons per hour. This limitation has been observed in our experience with delta robots deployed at collaborating facilities, where throughput bottlenecks significantly impacted overall system efficiency.

The industry faces particular challenges in recovering complex materials such as consumer batteries (Li-ion, Ni-based, Alkaline), critical materials from e-waste, mixed plastics, contaminated paper and cardboard, and multi-material packaging. The current technological limitations in processing these materials result in significant portions being diverted to landfills, representing both economic losses and environmental impacts [5]. Cross-contamination remains a persistent issue, as inadequate sorting precision leads to material stream contamination, substantially reducing the value of recovered materials. Additionally, current systems face a fundamental trade-off between processing speed and accuracy, unable to maintain high precision at increased throughput rates and high-costs. This technological gap has created a significant disparity between the theoretical recyclability of materials and actual recovery rates [6]. The combination of these limitations has resulted in a pressing need for technological advancement in the waste management industry. The gap between current capabilities and growing waste management demands highlights the necessity for innovative solutions that can address both efficiency and accuracy in material recovery processes.

Technology Approach

3.1 System Overview

The proposed technology leverages advanced artificial intelligence and specialized hardware components to revolutionize material recovery processes This research aims to develop an Artificial Intelligence (A.I.) based modular smart system that can be retro-fitted at existing Materials Recovery Facilities (MRFs) to identify, sort, and characterize MSW to generate high-quality secondary feedstocks. Fig 3 shows the modular system that comprises an A.I. light-box and multiple actuators that can simultaneously pick up materials from the conveyor belt and sort them for recycling.

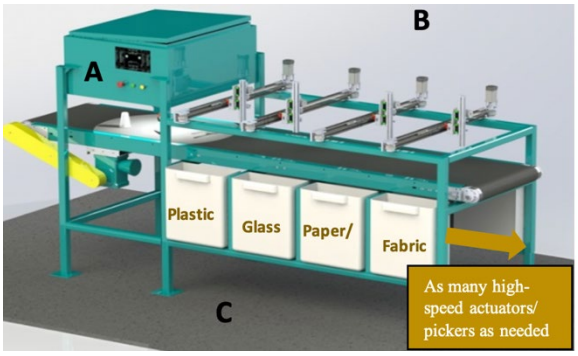


Figure 3: *Proposed high-speed A.I. based sorting system that can be retrofitted on existing conveyors for recovering valuable materials.*

3.2 Vision AI System Architecture

Figure 4: *Samples from our dataset. The material is acquired from our MRF partner Solid Waste Authority of Palm Beach, FL*

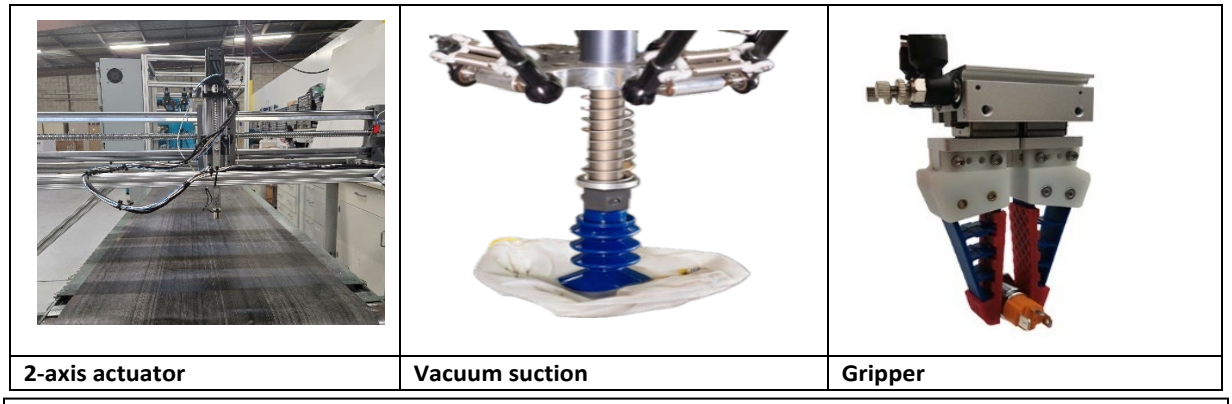
The vision AI process begins with high-resolution image acquisition at microsecond-level shuttle speeds, minimizing motion blur of objects on high-speed belt conveyors. These images undergo preprocessing with calibration and distortion correction before individual material pieces are identified and classified by the AI system. The process from image acquisition to AI decision-making is completed within 120 milliseconds, enabling real-time sorting operations.

The system's machine learning architecture, RecoverNet, builds upon YOLO [15] and EfficientNet's architecture [13] while incorporating self-attention mechanisms similar to transformer-based networks [16]. We utilize a segmentation algorithm like SAM [14] (that requires minimal training data) or fine-tuned algorithm with custom dataset like MaskRCNN [17] or YOLO 11 to achieve pixel-perfect segmentation of different materials within complex, cluttered scenes. Fig 4 shows sample images from our dataset. This allows our system to precisely delineate boundaries between different materials, handle overlapping and partially occluded items, identify multiple material types within a single object and maintain accuracy even with varying object sizes and orientations. For material classification, the segmented objects are processed through UHV's proprietary AI models for precise material classification, as depicted in Fig 5. The system can differentiate between various types of feedstocks including, different grades of paper and cardboard, various types of plastics (PET, HDPE, PVC, etc.), metals (ferrous and non-ferrous), glass (by color and type), batteries (by form factor) and fabrics and textiles, The result is significantly enhanced sorting accuracy while maintaining the speed necessary for industrial applications.

Figure 5: *Examples of what our A.I. models see. The software calculates the boundaries of different objects and this information is used by the robotic actuator to sort the material.*

3.3 Hardware Implementation

3.3.1: 2-Axis Actuator System



2-axis actuator	Vacuum suction	Gripper

Figure 6: *High-speed 2axis system on the left. Different end-effectors for picking up materials of different sizes and shapes. The grippers can be optimized for picking up different types of materials encountered.*

The hardware implementation centers on a sophisticated 2-axis actuator system featuring modified mounts for vertical axis movement and specialized end-effectors, including vacuum systems. The motion control is managed through a

MESA 7i96s Ethernet-connected board, an advanced motion control system designed for CNC and robotic applications. This board leverages FPGA technology to handle real-time tasks such as step generation and encoder counting with minimal latency, supporting up to five axes using step and direction signals. Various types of end-effectors are used for different types of materials like plastic, e-scrap, glass, and metals. Fig 6 shows our high-speed actuator with multiple end-effectors. These grippers can be optimized for picking up different types of scrap. For example, vacuum suction is ideal for paper and polythene bags while a mechanical finger actuator is better for picking up glass and hard plastics. These actuators, guided by the sorting system's input, can swiftly and accurately separate MSW into distinct categories for recycling, ensuring minimal cross-contamination and optimizing the recycling process.

3.3.2 Motor Control and Feedback Systems

The system employs both AC servo motor (Horizontal) and DC servo motor (Vertical) systems with sophisticated encoder feedback for closed-loop motion control. Motion control implementation is achieved through LinuxCNC operating on a real-time Linux environment with Preempt-RT kernel, ensuring consistent timing for motion commands and feedback processing. The MESA 7i96s board communicates via its built-in HostMot2 driver, facilitating precise step generation and encoder feedback at high speeds. Fig 7 shows the entire control system for one actuator.

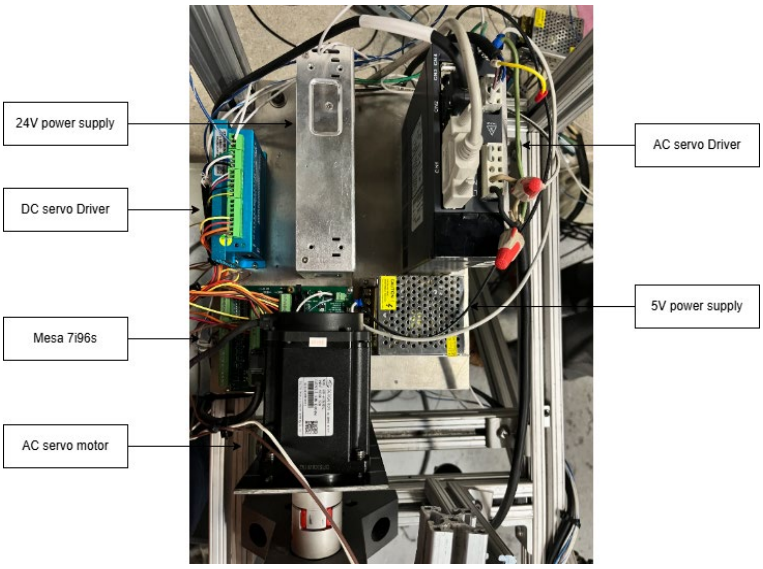


***Figure 7**: Internal components of the MESA 7i96s-based control system showing AC servo driver, DC servo driver, Mesa 7i96s board, and power supplies integrated into a compact control* cabinet.

The closed-loop control system integrates real-time encoder feedback from both motors, enabling precise position tracking through a PID control loop within LinuxCNC. This feedback mechanism actively corrects positioning errors, maintaining consistent performance despite variations in load or conveyor speed. The control architecture is enhanced through a custom Python functions using the LinuxCNC Python API, which dynamically adjusts Z-axis travel for varying material heights and synchronizes pickup sequences with conveyor speed. The system employs a standard trapezoidal velocity profile to determine motor movement timing from starting position to target location. As shown in Fig 8, this profile segments the motion into three distinct phases: acceleration from rest to maximum velocity, constant velocity cruising, and deceleration to the final position. This approach ensures smooth motion transitions while maintaining precise positioning accuracy.

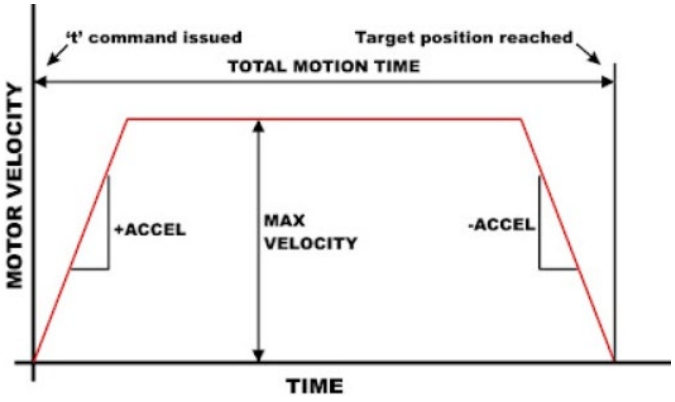


***Figure 8**: Trapezoidal velocity profile illustrating the motion control sequence of the actuator system from initial command to target position achievement.*

With our system's maximum velocity of 1500 mm/s and acceleration of 7,000 mm/s², the profile ensures minimal jerk while maintaining positioning accuracy within ±0.1mm. This adaptive profile ensures the actuator arrives precisely when and where needed for material pickup on the running conveyor. The integration

of carefully tuned motion parameters, real-time closed-loop control, and dynamic Python scripting enables reliable synchronization between pickup motions and conveyor movement while accommodating varying battery heights and positions. This comprehensive motion control strategy, combined with the PID feedback system, maintains consistent performance despite variations in load or conveyor speed.

Power management is implemented through a dedicated 5V DC supply for the board and 24V field power for industrial-grade I/O operations. Critical motor driver connections include Step+/Step- signals, enable lines, and encoder feedback (A+, A-, B+, B-), establishing a robust control loop. The system incorporates electromagnetic components powered through high-load I/O outputs, with flyback diode protection against inductive voltage spikes. This custom integration of hardware and software components ensures precise, reliable, and efficient material handling operations at lower costs.

3.3.3 Modular Design and Integration

Fig 9 shows the modular design of the A.I. system, photographs of the A.I. module and the robotic actuators recovering various materials from a mixed stream of waste. The modularity of this represents a significant

advancement in material recovery facility integration, allowing seamless incorporation into existing systems without extensive modifications. The system incorporates multiple high-speed mechanical actuators, each optimized for specific material properties through LinuxCNC compatibility. Custom end-effectors, including vacuum suction systems for paper and polythene materials and specialized grippers for glass and hard plastics, electromagnets for certain types of metals and e-scrap are managed through the MESA control board's configurable firmware. The cost-effectiveness of the custom actuators makes it possible to increase the number of actuators used thus increasing the efficiency of the system. The modular design, versatility in material handling, combined with the system's reliable real-time motor control and comprehensive feedback mechanisms, ensures efficient processing across diverse waste streams.

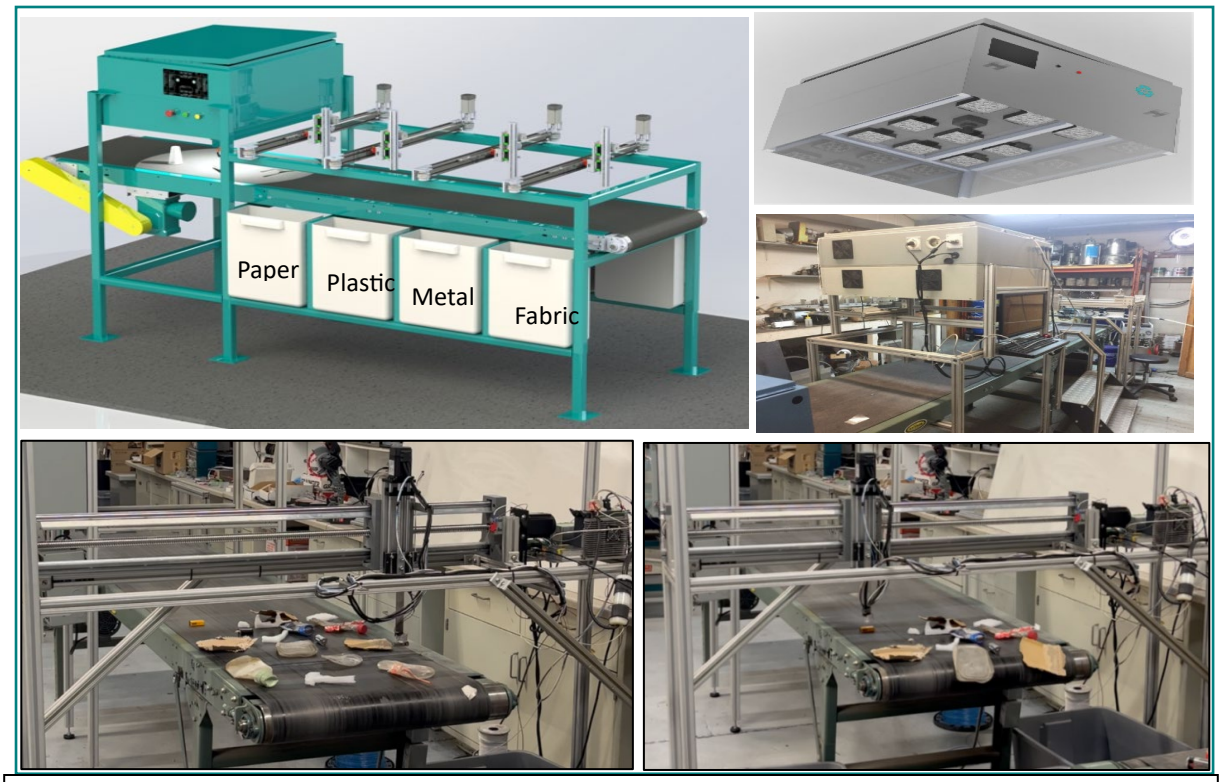


***Figure 9**: **(a)** A schematic diagram of proposed modular sorter with high speed, low-cost, linear robotic actuators to pick various materials and sort them into different bins. These actuators are 10-50 times faster and much lower cost than the 5-axis robotic arms, **(b)** a schematic of the A.I. module and **(c)** a photograph of the A.I. module retrofitted on a conveyor at UHV, **(d,e)** actuators in action picking up e-scrap from mixed waste stream at UHV*

3.4 Software Architecture

The software architecture has been enhanced to incorporate deep learning-based object detection specifically for identifying batteries in mixed waste streams. The control software manages real-time actuator positioning while processing encoder feedback data and monitoring safety systems. The integration of multi-axis coordination enables precise control over all system components, ensuring optimal performance during operation.

The development process follows three distinct phases. The first phase focuses on AI algorithm optimization for various material types, ensuring accurate identification and classification. The second phase involves hardware and software modification to accommodate different material sizes and types, while the final phase encompasses system integration and demonstration at MRFs. This systematic approach ensures robust performance while maintaining scalability and cost-effectiveness in real-world applications.

Discussion

The development and implementation of the AI-driven material recovery system represents a significant advancement in waste management technology, addressing several critical challenges in the recycling industry. The system's ability to process multiple material streams simultaneously while maintaining high accuracy demonstrates the potential for transformative impact in Materials Recovery Facilities (MRFs). The integration of advanced AI algorithms with custom-built actuators has shown promising results in overcoming traditional sorting limitations. Unlike conventional robotic or optical sorters which require multiple passes for material-specific classification, this system performs sorting in a single pass with higher throughput and precision. Multi-axis robotic arms in use today generally operate at lower pick rates (estimated at 40–60 picks/min based on vendor specifications) and require significant infrastructure investment [10][9]. In contrast, our system can deliver 80-120 picks/min (standard conveyor), supports multi-material classification at 90-95% accuracy, and is modular and cost-efficient—making it ideal for scalable industrial deployment.

Furthermore, accurate sorting of materials from complex mixed waste streams often requires multiple robots and end-effectors to handle the diverse objects as highlighted in [9]. This is not feasible with the current high-cost robots. Our system addresses this challenge by allowing each actuator to be customized for a specific material type, accounting for its unique weight, shape, and handling characteristics. This modular flexibility enables efficient and precise recovery, further enhancing cost-effectiveness and reducing system complexity. While the current robotic system can recover waste to a certain extent, our system can ensure no valuable items end up in landfills.

The modular design approach proves particularly valuable for industry adoption, allowing facilities to upgrade their capabilities without requiring complete infrastructure overhaul. This architectural decision addresses a key barrier to technological advancement in the recycling industry: the high cost of facility modernization. The system's ability to retrofit existing conveyor systems makes it an economically viable solution for facilities of varying scales. Performance data indicates that the machine learning architecture, particularly the RecoverNet implementation, achieves high accuracy in material identification while maintaining industrial-grade processing speeds. The incorporation of transformer-based networks and spatial transformers has proven effective in handling the variability inherent in waste streams, though challenges remain in processing heavily contaminated or damaged materials. The decision to implement a 2-axis actuator system with specialized end-effectors demonstrates an effective balance between complexity and functionality. While more degrees of freedom might offer greater flexibility, the current design achieves the required manipulation capabilities while maintaining system reliability and cost-effectiveness. The MESA 7i96s control system's integration provides the necessary precision for high-speed sorting operations, though careful calibration and maintenance procedures are essential for optimal performance.

Conclusions & Recommendations

This research presents a novel AI-driven approach for efficient recovery of resources like metals, e-scrap, plastics, textile and batteries from municipal solid waste, demonstrating significant improvements over traditional sorting methods. The integration of advanced image-based AI algorithms with custom-built robotic actuators has shown promising results in achieving high-throughput, precise, and scalable material recovery. The system's unique one-pass recovery approach, coupled with its modular design for easy MRF integration, addresses critical challenges in the waste management industry while supporting the transition toward a more circular economy. The demonstrated ability to simultaneously process multiple material streams while maintaining high accuracy and cost-effectiveness positions this technology as a viable solution for transforming waste management infrastructure.

For future development and implementation, we recommend focusing on three key areas: expanding the system's material recognition capabilities through continuous AI model training with more diverse datasets, scaling the technology for higher throughput applications while maintaining sorting accuracy, and developing additional specialized end-effectors for handling emerging material types. Furthermore, establishing partnerships with MRFs for extended field testing would provide valuable operational data and insights for system optimization. These improvements would enhance the system's commercial viability and its contribution to sustainable resource recovery practices.

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