DEVELOPMENT OF AN ECONOMICALLY VIABLE AI-ENABLED SORTING TECHNOLOGY FOR COMPLEX PLASTIC WASTE STREAMS

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Abstract: This paper presents a novel, economically viable approach to addressing two critical challenges in plastic recycling: the sorting of complex #3-#7 plastic waste streams and the detection of polyvinyl chloride (PVC) contamination in mixed plastic waste. Building upon successful implementations in metal sorting from the ARPA-E METALS project, our research explores the integration of artificial intelligence with multi-sensor data collection, aiming to develop a comprehensive sorting solution. **This patented technology (US Patent 11,969,764, 2024; US Patent US20240109103A1)** eliminates the need for expensive sensor arrays during operational deployment while maintaining high classification accuracy. Advanced A.I. models, including ResNet50 and EfficientNet, were trained on comprehensive datasets to accurately identify various plastic types. These models utilized image datasets collected using low-cost sorting equipment, with ground truth verified manually as well as through multi-sensor equipment including Near-Infrared (NIR), Mid-Infrared (MIR), and X-Ray Fluorescence (XRF) techniques to enhance detection reliability across varying environmental conditions and contamination levels. The resulting models demonstrated high performance on test streams of mixed materials, achieving 92% accuracy and efficiency, significantly surpassing conventional methods in accuracy and reliability. Our methodology consists of three key components: (1) initial multi-sensor fingerprinting for comprehensive material characterization, (2) development of novel classification hierarchies using both supervised and unsupervised learning approaches, and (3) training of a vision-based CNN that replicates chemical-based sorting decisions. Our technology demonstrates significant cost reduction compared to conventional multi-sensor systems through simplified hardware requirements and optimized processing, while maintaining high-throughput sorting capabilities at 60 pieces per minute. The system achieves processing costs of $20-30 per ton, demonstrating commercial viability. This integration of AI-driven solutions into MRFs offers transformative potential, enabling low-cost, automated, and scalable plastic identification and separation. The system's effectiveness has been validated through extensive industrial trials, demonstrating its capability to create valuable material streams for various applications, including chemical recycling feedstocks, automotive parts, and packaging materials. The developed classification system enables the creation of novel, market-driven material streams from previously non-recyclable plastics, potentially unlocking new market opportunities worth an estimated $2-3 billion annually in the United States alone. This research represents a significant advancement in recycling technology, offering a practical solution to both technical and economic challenges in plastic waste sorting. Our comprehensive dataset, combining visual and spectroscopic information, positions this work for future developments in multi-sensor fusion approaches. The findings highlight the feasibility of incorporating such intelligent systems into existing recycling workflows while minimizing additional operational costs, supporting the transition toward a more sustainable circular economy and enabling the recovery and reuse of materials currently destined for landfills or incineration. This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under award number DE-EE0009266.

Introduction and Motivation

The global plastic waste crisis presents an increasingly urgent challenge for environmental sustainability and resource management. With annual plastic production exceeding 400 million tonnes and only 9% being recycled effectively, the need for innovative recycling solutions has never been more critical [13]. This challenge is particularly evident in the recycling of mixed plastic waste streams, where complex materials such as multi-layer polymers, composite materials, and PVC contamination significantly impact recycling efficiency and output quality [5, 8].

Traditional recycling facilities face two interconnected challenges: first, the accurate identification and separation of complex #3-#7 plastics, and second, the effective management of contaminants, including PVC, which can severely compromise the quality of recycled materials [2, 5]. The greatest limitations in current sensor-based sorting technologies arise from reliance on single-sensor approaches, as each sensor type can only detect a narrow range of signals. While Near-Infrared (NIR) spectroscopy can identify single polymers with high accuracy, it cannot detect black plastics or multilayered materials. Similarly, Mid-Infrared (MIR) can identify black plastics but struggles with multi-layer materials, and X-Ray Fluorescence (XRF) can measure inorganic chemical composition but cannot identify organic components [7, 14].

Recent advances in artificial intelligence (AI) and machine learning have shown promising potential in revolutionizing waste management and recycling processes [1, 4, 15]. This potential was first demonstrated in metal sorting through the ARPA-E METALS project in 2013, which established the foundational approach for using AI in material sorting applications. The success in metal sorting has opened new possibilities for plastic waste management, particularly in creating novel fractions from existing waste streams, increasing fraction purity, removing contaminations, and reducing sorting costs [11, 12].

The economic implications of improved plastic sorting technologies are substantial. The market for recovered materials, particularly in the United States, represents a potential $2-3 billion annual opportunity [6]. Current advanced sorting technologies must balance several competing factors. First, the need for high-accuracy material identification. Second, requirements for industrial-scale processing speeds. Third, capital and operational cost constraints and last, market demands for consistent, high-quality output streams [9, 10]. Table 1 presents the different sensor types used in sorting systems, along with their associated physical principles and the specific signals they detect for material identification and classification. Our research addresses these challenges through a novel approach that combines the advantages of multi-sensor data collection with cost-effective, vision-based deployment systems. By utilizing comprehensive datasets that include visual, NIR, MIR, and XRF spectroscopic data, we have developed a system that achieves high accuracy in plastic identification while maintaining economic viability for industrial implementation [3].

Sensor Type	**Associated Physics**	**Detected Signal**
Eddy Current	Magnetic Field	Metals
Visible Camera	Visible Light Reflection	Different colored materials
X-Ray Transmission	X-Ray Intensity	Transmission, Density
Near Infrared	IR Spectrum	Polymer type
XRF	XRF Spectrum	Inorganic elemental composition

Table 1: Most common sensors found in sorting technologies

This paper makes the following key contributions to the field:
1. Development of a comprehensive plastics dataset combining visual and spectroscopic information.
2. Implementation of advanced deep learning models achieving 92% accuracy in plastic type identification
3. Validation of the system's effectiveness through extensive industrial trials

The remainder of this paper is organized as follows: Section 2 examines the current state of the technology industry uses, providing context for existing solutions and their limitations; Section 3 details our technology approach and system architecture; Section 4 presents a comprehensive discussion of our results and their implications; and Section 5 concludes with recommendations and future directions for the industry.

Current State of the Technology Industry Uses

The current plastic recycling industry relies heavily on conventional sorting technologies that, while functional, struggle to address the increasing complexity of modern plastic waste streams. This section examines the current technological landscape, its limitations, and the economic framework within which these technologies operate. The predominant sorting technologies in materials recovery facilities (MRFs) center (such as Solid Waste Authority of Palm Beach County, Florida) around NIR spectroscopy, which has established itself as the industry standard for polymer identification. NIR technology successfully separates PE film from other plastics and enables sorting of rigid plastics into PP, PE, PET, and PS streams [4]. However, these systems face significant limitations, particularly with black plastics containing carbon black additives [9] and materials affected by environmental factors such as moisture and temperature variations [5]. The capital investment required for these systems remains substantial, with even portable NIR units costing approximately $16,000 [1]. The complexity of modern plastic waste streams, particularly multi-layer materials, presents a significant challenge to current sorting technologies. Multi-layer structures typically comprise three or more layers, including combinations of polyolefins, PET, PVDC, PA, EVOH, aluminum, and paper

[3]. The recycling industry currently struggles with approximately 2.6 million tons of multilayer packaging annually, much of which ends up incinerated or in landfills due to the complexity of classification, layer separation, and high treatment costs [3].

Current sorting facilities operate under stringent economic constraints. Analysis indicates that plastic recycling costs approximately $500 per ton to earn a 10% Internal Rate of Return (IRR) on $1000 per ton of capital expenditure for a mechanical recycling facility [6]. Major cost components include capital equipment, energy consumption, labor for precise sorting, and transportation of plastic waste. Additionally, facilities must continually expand their sorting capabilities, with projections indicating the need for additional sorters to handle increasing tonnage from commercial and curbside plastic bottle collection programs [2]. The industry has begun exploring multi-sensor approaches to address these challenges. The combination of XRF, NIR, and FTIR technologies has shown promise in providing comprehensive elemental, mineral, and molecular analyses [5]. However, implementing such multi-sensor systems presents its own challenges, including increased capital costs and system complexity. The Niton XL5 Plus handheld XRF analyzer represents current capabilities in elemental composition analysis of various materials, including metals, scale, sludge, oil, powders, and slurries [5].

Market demands increasingly drive sorting requirements, particularly in high-value applications such as food packaging. Current industrial standards require the recovery of five distinct plastic fractions with material loss below 20% and sorting precision exceeding 95% [4]. For food contact applications, European quality standards mandate extremely high purity levels, with contamination from biodegradables and PVC restricted to less than 0.3% [4]. These stringent requirements, coupled with the technical limitations of current sorting technologies, create a significant gap between industry capabilities and market demands. Leading facilities worldwide demonstrate both the potential and limitations of current technologies. The SITE ZERO facility in Motola, Sweden, and ***the SORTERA Markel facility in Indiana showcase state-of-the-art sorting capabilities*** [3]. These installations also highlight the ongoing challenges in achieving consistent, high-quality output while maintaining economic viability. The industry's reliance on single-sensor approaches, despite their known limitations, underscores the need for innovative solutions that can address both technical and economic constraints simultaneously.

Technology Approach

Sensor Technologies Integration

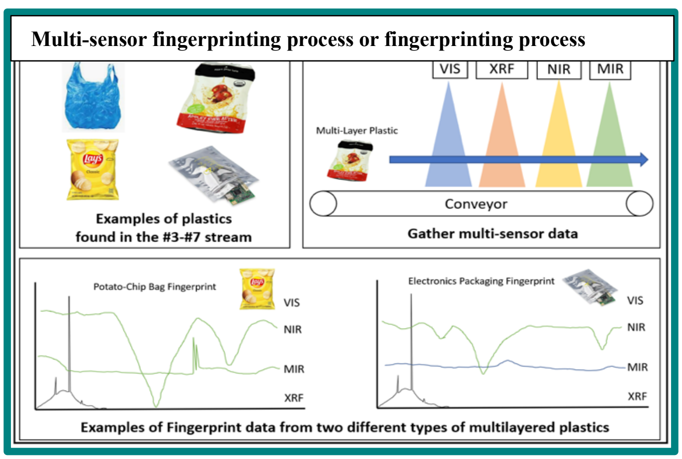


Figure 1: Multi-sensor data collection process thru XRF, NIR, and MIR sensors create material 'fingerprints' establishing ground truth classification of plastic types., with parallel visual data capture for CNN training

Our technology approach integrates multi-sensor data collection with vision-based implementation while maintaining economic viability as shown in Figure 1. The methodology encompasses sensor integration, data acquisition, classification development, and practical deployment. The system incorporates four specialized sensing technologies. The KUSTA LLA 1.7 and 1.8 NIR systems operate in the 1100-1700nm range with 7nm spectral resolution, achieving 30-70 frames per second through temperature-stabilized InGaAs detectors [23]. The Amtek XRF analyzer [24] provides elemental detection from sodium to uranium using a 50kV X-ray tube with Rh target and 25mm² silicon drift detector. The Specim MIR FX50 system operates in the 2.5-5.0 μm range with 10 cm^{-1} resolution [25]. Visual data comes from Basler ace cameras providing 1920 x 1200 resolution at 150 fps through Sony IMX174 CMOS sensors. [26]

Data Acquisition System

The data acquisition system, as shown in Figure 3, integrates multiple line-scanning cameras through a sophisticated high-throughput pipeline developed specifically for real-time material classification. The system simultaneously collects data from two Basler RGB cameras, two NIR cameras operating in 1.7 and 2.2 nm ranges, and one MIR camera, all synchronized through precise timing controls. Figure 2 shows the mixed plastic bales along with the sensor spectrum for detection.

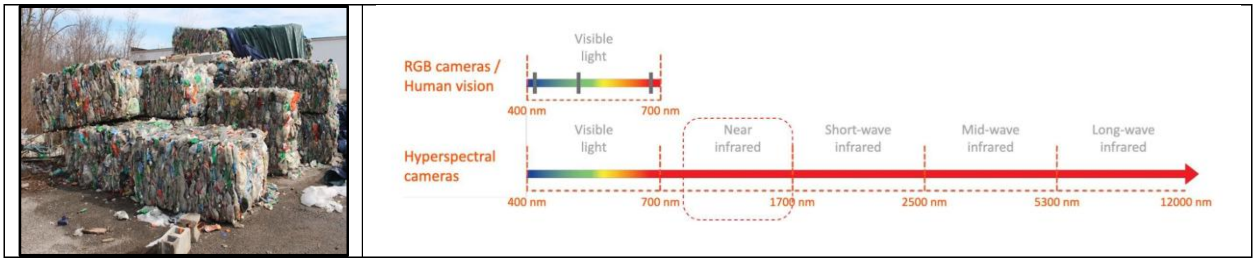


Figure 2: (Left) Mixed plastic waste bales from SWA, Florida MRF facility, showing typical input material containing various plastic types. (Right) Electromagnetic spectrum showing operational ranges of system sensors: visible light (cameras, 400-700nm), Near-Infrared (1100-1700nm), Mid-Infrared (2500-5000 nm) regions

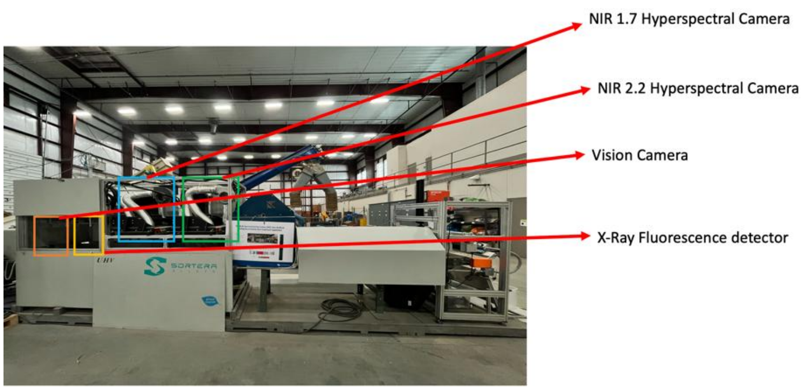


Figure 3: ***Multi Sensor Sorter located at Idaho National Lab f****or plastic sorting: NIR 1.7 Hyperspectral Camera, NIR 2.2 Hyperspectral Camera, Vision Camera, and X-ray Fluorescence detector positioned above the conveyor system for simultaneous data collection.*

The UDP communication protocol enables high-speed data collection, with each IR device operating through dedicated Ethernet interfaces to manage bandwidth requirements. Custom Python-based software maintains circular buffers for hyperspectral image formation, with buffer dimensionality—including line width, number of channels, and number of lines—specified during class instantiation. This approach prevents unnecessary memory allocation and deallocation, optimizing system performance. The LLA NIR camera systems stream raw data over UDP to a remote host, where our software forms two-dimensional in-memory hyperspectral images. The MIR line scanner integration required development of a C++ translation program utilizing the SDK to convert data into a UDP-compatible stream, ensuring consistent data handling across all IR devices. This unified approach enables simultaneous real-time data collection from all three infrared devices. Sample detection utilizes a Wenglor OPT2003 laser system [27], providing continuous DC voltage signals for precise timing determination. The system calculates start and end times for each sample, generating unique object IDs based on detection timing. These IDs are distributed to all cameras using Python's multiprocessing queue system. The current estimated rate of data collection is **~60 samples per minute** with the bottle neck being the time taken for the RGB camera to capture an image. While testing the data collection rate, it was identified that clear (transparent) plastics were either missed by the laser or perceived

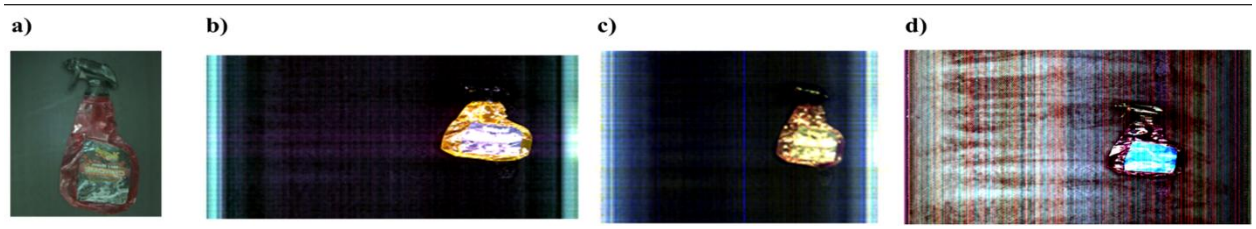


Figure 4: Images from all the cameras for a plastic waste sample. The RGB image in a) for the sample and the corresponding false-colored images from b) NIR 1.7, c) NIR 2.2, and d) MIR hyperspectral cameras

as multiple samples due to the signal from the laser (20 of 20 samples). When one sample is perceived to be multiple samples, it results in duplicate images being recorded for that sample. Real-time signal processing techniques, including smoothing and convolution, improve detection accuracy particularly for transparent plastics, reducing misdetection rates to less than 5% (1/20 samples). This improvement increased the precision of sample detection by the laser where only 1/20 samples were either missed or perceived to be multiple samples.

Vision-Based Implementation

Our implementation builds upon multi-sensor data characterization to establish accurate material classification. The system correlates NIR polymer identification, MIR surface chemistry data, and XRF elemental analysis to create comprehensive material profiles, enabling classification of complex materials including multi-layer packaging and black plastics. This classification framework guides the development of our vision-based sorting system as shown in Figure 5. The implementation leverages synchronized image capture under precisely controlled LED illumination conditions. The preprocessing pipeline incorporates multiple stages of image processing to ensure robust classification performance. Initial processing begins with color normalization using calibrated reference cards, followed by dynamic background subtraction with adaptive thresholding. Images are standardized to 224x224 pixels, and comprehensive data augmentation techniques are applied to enhance model robustness, including controlled rotations, brightness variations, and Gaussian noise injection.

Figure 5: Vision based plastic dataset collection and sorting machine at UHV, Fort Wayne, Indiana.

The deep learning architecture integrates three complementary neural networks, each serving a specific role in the classification pipeline. YOLO v5 [28] serves as the primary object detection system, operating at 640x640 pixel resolution with optimized confidence and IoU thresholds specifically tuned for plastic materials. This initial detection stage ensures accurate object localization and segmentation before detailed classification. The classification system employs a modified ResNet-50 architecture [28] featuring custom input layers and additional batch normalization to handle the specific characteristics of plastic materials. The network architecture was optimized through extensive experimentation, with training parameters carefully selected to balance accuracy and computational efficiency. Running in parallel, an EfficientNet-B4 [28] implementation provides complementary classification capabilities through its compound scaling approach. This dual-network configuration enables robust feature extraction across varying material types and environmental conditions.

Training Methodology and System Performance

The system implementation utilized Ubuntu 22.04 with CUDA 11 framework on consumer-grade hardware: an AMD Ryzen 7 processor, 32GB RAM, and NVIDIA GTX 1080 GPU, demonstrating cost-effective deployment potential. The dataset comprises 33,387 images distributed across five plastic categories: Type 5 (PP) forms the largest class with 10,393 samples, followed by Type 2 (HDPE) with 7,935 and Type 1 (PETE) with 7,246 samples. Type 5/7 (Mixed) contains 6,345 samples, while Type 3 (PVC) represents the smallest class with 1,468 samples, highlighting the inherent class imbalance in real-world plastic waste streams. Training utilized a dataset of 33,000 images, split into 70% training, 20% validation, and 10% testing sets. Data augmentation techniques included random flipping, blurring, sharpening, cropping, auto-contrast, affine transformations, jittering, equalization, pasteurization, and adversarial noising. Two parallel deep learning networks were implemented: ResNet and EfficientNet, with transfer learning from ImageNet pre-trained weights. Given the unbalanced nature of our dataset, where certain plastic types were more prevalent than others, we selected multiple evaluation metrics to provide comprehensive performance assessment. Accuracy alone could be misleading for unbalanced datasets; thus we employed precision to measure false positive rates, recall for false negative rates, and F1 scores to balance both metrics. Model interpretability was enhanced through visualization techniques. GradCAM analysis highlighted regions of visual input significant to classification decisions, providing insights into feature importance for different plastic types. t-SNE plots visualized high-dimensional feature spaces, revealing clustering patterns among different material categories as in Figure 6 and7.

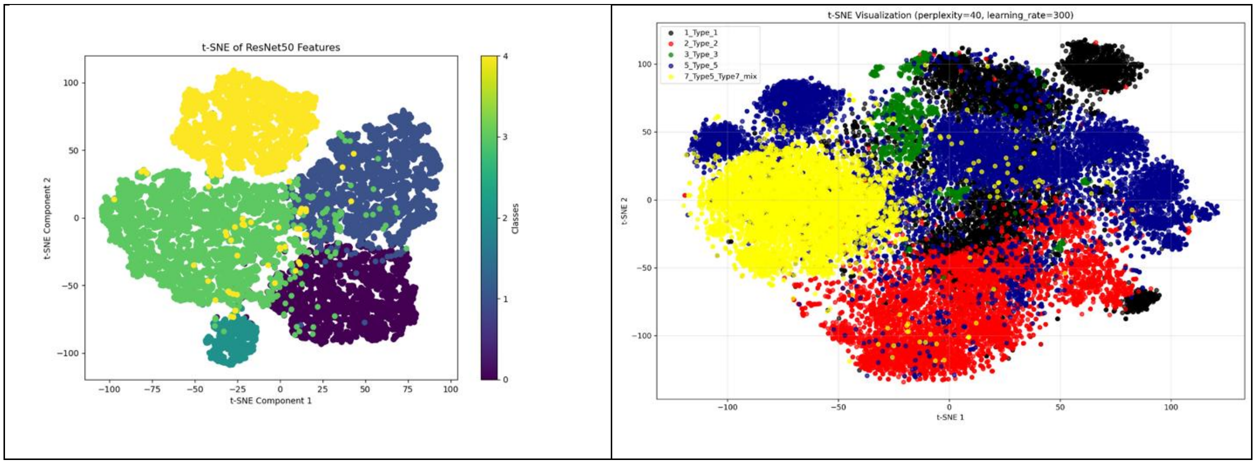


Figure 6: t-SNE visualization of feature embeddings from ResNet (left) and EfficientNet (right) models, demonstrating material clustering patterns. Colors represent different plastic types.

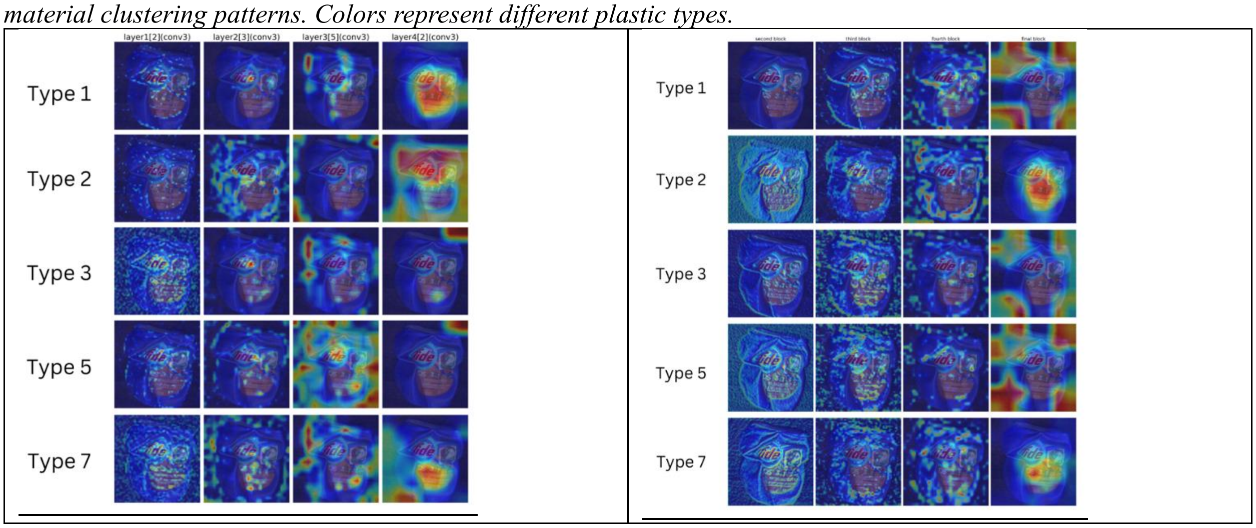


Figure 7: GradCAM visualization highlighting critical regions in plastic images that influence the model's sorting predictions, aiding in the interpretability of plastic classification

	EfficientNet				ResNet-50		
Material Type	**Precision**	**Recall**	**F1 score**		**Precision**	**Recall**	**F1 score**
Type 1 (PETE)	96.15	85.45	90.48		93.90	85.45	90.52
Type 2 (HDPE)	87.42	96.10	91.55		85.42	87.14	89.65
Type 3 (PVC)	47.62	66.67	55.56		43.32	42.86	52.13
Type 5 (PP)	90.84	90.18	90.51		92.21	92.53	92.12
Type 5/7 (Mix)	96.78	98.49	97.63		92.48	93.74	93.83

Table 2: Comparison of model performance metrics between EfficientNet (left columns) and ResNet (right columns). EfficientNet achieves 91.85% accuracy with 0.385ms inference time, while ResNet shows 87.19% accuracy with 0.225ms inference time. Type 3 (PVC) classification shows lower F1 scores due to dataset imbalance, while both models demonstrate strong performance (F1>90%) for other categories.

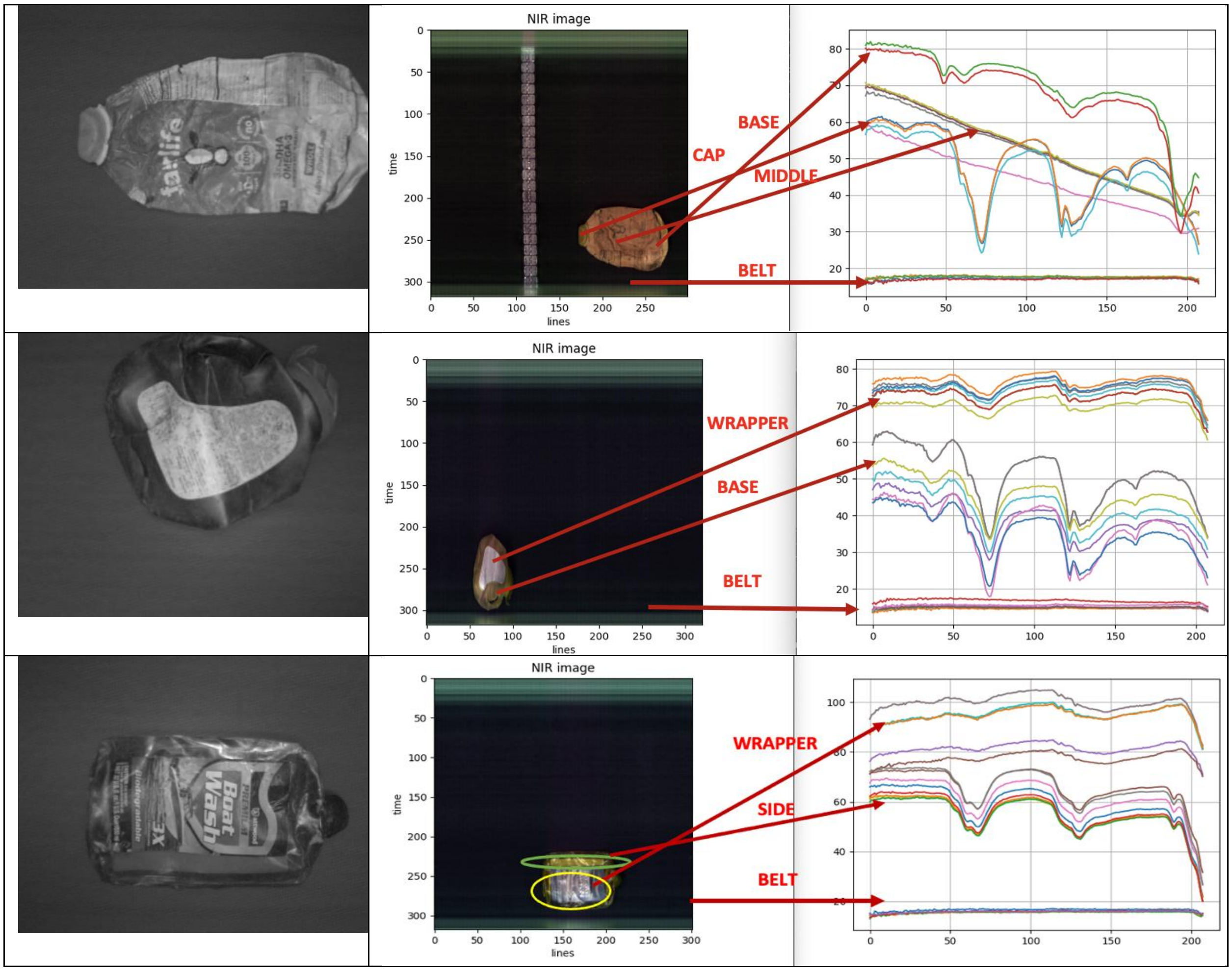
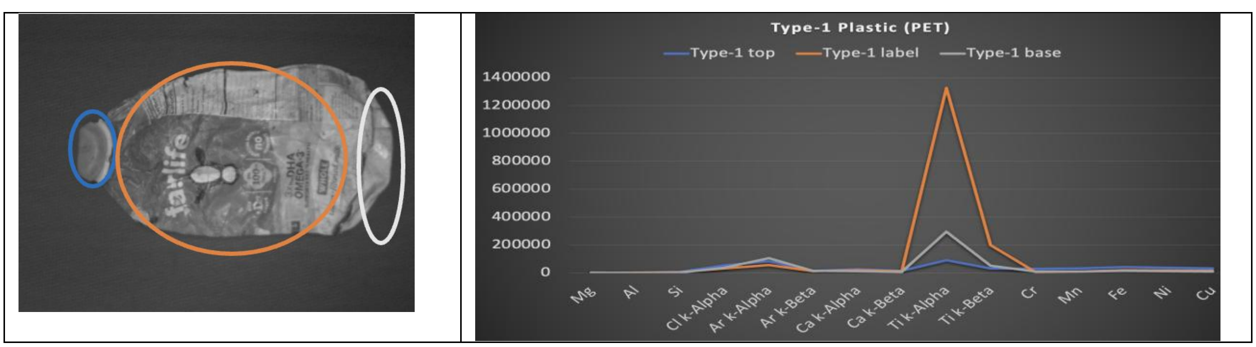


Figure 8: Analysis of a plastic bottle using NIR for Type 1 (PET) , Type 2 (HDPE) and Type 3 (PVC), showing (left) visible image, (middle) NIR line scan data, and (right) spectral signatures from different regions (base, cap, middle, and belt) of the bottle.



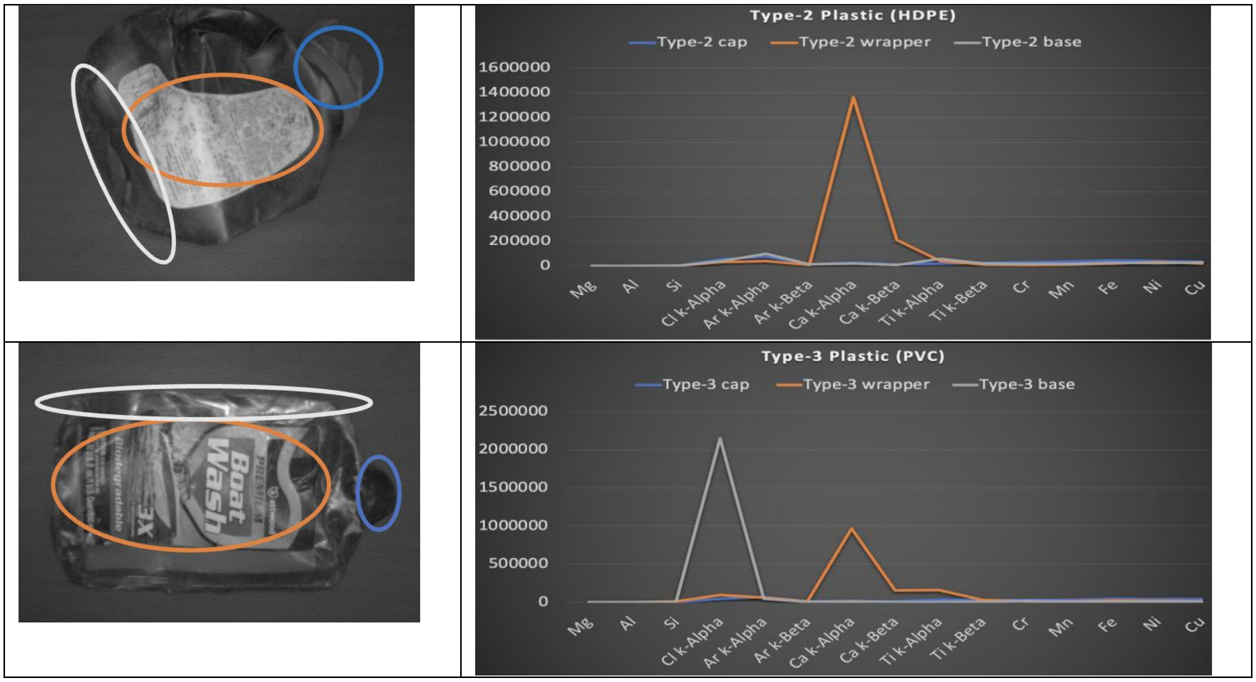


Figure 9: X-ray spectroscopy analysis of plastic bottle for Type 1 (PET) , Type 2 (HDPE) and Type 3 (PVC), showing visible image, (left) and segmented X-ray image (right) highlighting three distinct regions - cap, wrapper, and base, and corresponding elemental composition spectrum demonstrating characteristic peaks for each component

Practical Implementation Challenges and Solutions

Industrial deployment required addressing several key challenges to maintain laboratory-level accuracy in real-world conditions. Material presentation variations in MRF conveyor systems were addressed through a dynamic image capture system that adjusts exposure times based on conveyor speed and material flow. Environmental challenges were mitigated using a custom-designed lighting enclosure with high-frequency LED illumination synchronized to camera capture timing, protecting optical components while ensuring consistent imaging under variable conditions. To handle random material orientations and potential overlapping, we implemented two solutions: mechanical separation via vibratory feeders and YOLO-based detection for consistent segmentation of partially overlapped materials. System performance was optimized through GPU acceleration and parallel processing streams, while automated calibration routines using standard reference materials minimize operational disruptions. Techno-economic analysis (TEA) and Life Cycle Assessment (LCA) studies identified optimal MRF locations for technology deployment, considering factors such as waste stream volumes, transportation costs, and regional market demands. This analysis ensures maximum economic benefit while minimizing environmental impact, supporting sustainable implementation of the sorting technology.

Discussion

Our research advances plastic waste sorting technology through a comprehensive dataset of 33,387 images across five plastic categories, with Type 5 (PP) comprising the largest class (10,393 samples) and Type 3 (PVC) the smallest (1,468 samples). Despite this class imbalance, our vision-based system achieves 91.85% accuracy with EfficientNet and 87.19% with ResNet, with inference times of 0.385ms and 0.225ms per sample respectively. The accuracy is calculated based on the standard definition as in [28]. The implemented system addresses key industry challenges through cost-effective hardware (consumer-grade GPU, 32GB RAM) while maintaining high classification accuracy. EfficientNet demonstrates F1 scores above 90% for most categories, with Type 5/7 achieving 97.63%. The multi-sensor approach for ground truth establishment, combined with vision-based deployment, offers a practical solution for industrial implementation. Technical analysis through t-SNE visualizations confirms effective feature learning, while GradCAM provides interpretability of model decisions. The system's ability to operate at industrial speeds (60 pieces/minute) while maintaining accuracy demonstrates its practical viability. TEA and LCA studies validate optimal deployment locations, supporting the technology's potential $2-3 billion market opportunity in the United States [6]. These results also highlight areas for continued development. While effective for most categories, Type 3 (PVC) classification shows lower accuracy (F1: 55.56% for EfficientNet, 52.13% for ResNet), primarily due to dataset imbalance with only 1,468 PVC samples. Our multi-sensor setup proves crucial for establishing reliable ground truth, particularly for materials indistinguishable by visual inspection alone, such as multi-layer packaging or plastics with similar appearance but different chemical compositions. This comprehensive characterization through NIR, MIR, and XRF enables accurate labeling of complex materials that would be impossible to classify using traditional single-sensor approaches. Environmental controls, particularly lighting conditions, remain critical for optimal performance, suggesting the need for enhanced robustness in variable industrial settings. Industrial implementation requires strategic integration with existing MRF infrastructure. Our approach addresses key practical considerations through automated calibration routines and dynamic image capture systems. However, successful deployment depends on maintaining consistent input material quality and establishing standardized operational protocols. The technology's broader impact extends to circular economy objectives. By enabling efficient sorting of previously challenging materials, particularly dark or multi-layer plastics, the system supports higher recycling rates and improved material recovery. The demonstrated performance on consumer-grade hardware suggests potential for widespread adoption across various facility scales, contributing to more accessible recycling infrastructure development.

Conclusions & Recommendations

This research demonstrates successful implementation of an AI-driven, vision-based plastic sorting system achieving 92% accuracy via vision based AI models, while operating at industrial speeds of 60 pieces per minute. UHV demonstrate the final cost metrics of less than \$30 - \$20 per ton for processing the material, confirming commercial viability. Future development should focus on three key areas: technical enhancement, industry implementation, and market development. Technical priorities include expanding capabilities for complex multi-layer materials through enhanced datasets and adaptive learning mechanisms. Industry implementation requires standardized integration protocols and comprehensive operator training programs. Market development needs collaboration with end-users for material specifications and certification standards. The demonstrated success in combining high accuracy with cost reduction provides a practical pathway for advancing plastic recycling technology. Future research should explore distributed systems and edge computing implementations to further improve accessibility for smaller recycling operations, supporting broader adoption of AI-driven sorting solutions in the circular economy. The **future work will include targeted dataset expansion** to improve performance for underrepresented and high-impact classes like PVC

Acknowledgements

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