AI-enabled robotic sorting for circular textile waste management: A scalable solution for India's recycling sector

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ABSTRACT – REZUMAT

AI-enabled robotic sorting for circular textile waste management: A scalable solution for India's recycling sector

The global textile industry faces a critical inflexion point as circular economy mandates intensify and waste volumes soar beyond 100 million tonnes annually. Central to realising circularity is the efficiency and fidelity of textile waste sorting, a longstanding bottleneck dominated by manual, low-throughput, and error-prone methods. This paper investigates the deployment of an AI-enabled robotic sorting system integrating hyperspectral imaging (HSI) and deep learning algorithms within the context of India's fragmented textile recycling ecosystem. We demonstrate that spectral imaging combined with convolutional neural networks (CNNs) achieves over 95% classification accuracy across heterogeneous, post-consumer Indian textile waste streams, including multi-fibre blends that typically confound manual sorters. Drawing from industrial benchmarks such as Sweden's SipTex and U.S.-based Refiberd, we design a prototype that integrates conveyor automation, real-time classification, and robotic actuation. Comparative analysis reveals that the AI system achieves throughput rates exceeding 1,000 garments per hour, representing a 20× gain over manual processes while reducing misclassification rates by more than 60%. A techno-economic model suggests payback periods under four years when scaled to medium-sized facilities, with significant reductions in labour dependency and waste-to-landfill ratios.

Our findings have strong implications for policy and industry: AI sorting systems not only align with India's National Textile Policy and MITRA initiatives but also represent an enabling infrastructure for chemical recycling, extended producer responsibility, and traceable material flows. By bridging technological innovation with operational scalability, this study advances the industrial feasibility of circular textiles in the Global South.

Keywords*: AI sorting, hyperspectral imaging, textile recycling, circular economy, robotic automation, India*

Sortarea robotizată bazată pe inteligență artificială pentru gestionarea circulară a deșeurilor textile: o soluție scalabilă pentru sectorul reciclării din India

Industria textilă globală se confruntă cu un punct critic de inflexiune, pe măsură ce mandatele economiei circulare se intensifică, iar volumele de deșeuri depășesc 100 de milioane de tone anual. Elementele esențiale pentru realizarea circularității sunt eficiența și fidelitatea sortării deșeurilor textile – un blocaj persistent, dominat de metode manuale, cu randament redus și predispuse la erori. Acest studiu de cercetare investighează implementarea unui sistem robotizat de sortare bazat pe inteligență artificială, care integrează imagistica hiperspectrală (HSI) și algoritmi de învățare profundă în contextul ecosistemului fragmentat de reciclare a textilelor din India. Demonstrăm că imagistica spectrală combinată cu rețele neuronale convoluționale (CNN) atinge o precizie de clasificare de peste 95% în fluxuri eterogene de deșeuri textile indiene post-consum, inclusiv amestecuri multi-fibre care de obicei se confundă de către sortatoarele manuale. Pornind de la repere industriale precum SipTex din Suedia și Refiberd din SUA, am proiectat un prototip care integrează automatizarea benzilor transportoare, clasificarea în timp real și acționarea robotică. Analiza comparativă arată că sistemul bazat pe inteligență artificială atinge rate de producție care depășesc 1.000 de articole de îmbrăcăminte pe oră, reprezentând un câștig de 20 de ori față de procesele de producție manuale, reducând în același timp ratele de clasificare greșită cu peste 60%. Un model tehnico-economic sugerează perioade de recuperare a investiției sub patru ani atunci când este scalat la instalații de dimensiuni medii, cu reduceri semnificative ale dependenței de forță de muncă și ale ratei de depozitare a deșeurilor.

Concluziile noastre au implicații puternice pentru politici și industrie: sistemele de sortare cu inteligență artificială nu numai că se aliniază cu politica națională privind industria textilă a Indiei și inițiativele MITRA, dar reprezintă și o infrastructură care să permită reciclarea chimică, responsabilitatea extinsă a producătorului și fluxurile de materiale trasabile. Prin combinarea inovației tehnologice cu scalabilitatea operațională, acest studiu promovează fezabilitatea industrială a textilelor circulare în Sudul Global.

Cuvinte cheie*: sortare prin inteligență artificială, imagistică hiperspectrală, reciclare textile, economie circulară, automatizare robotică, India*

INTRODUCTION

The Sustainability Imperative in Textiles

The textile industry, long celebrated for its economic dynamism and employment generation, now finds itself at the centre of a sustainability reckoning. Globally, the sector accounts for approximately 10–11% of greenhouse gas emissions and consumes over 93 billion cubic meters of water annually, ranking just behind agriculture in freshwater intensity [1]. Fast fashion, overproduction, and shortened product lifecycles have led to a surge in consumption. Over 100 million tonnes of textiles are produced annually, of which an estimated 75% end up in landfills or incinerators [2]. This escalating footprint has triggered both public and regulatory responses. The European Commission's Circular Economy Action Plan, along with Extended Producer Responsibility (EPR) mandates emerging in France, Sweden, and now India, signal a global transition toward closed-loop systems [3]. These initiatives aim not merely to promote recycling, but to decouple economic growth from raw material extraction, and position textile waste as a feedstock for circular innovation. In this policy landscape, sorting becomes the linchpin of the operational bottleneck that determines the quality, recoverability, and economic value of textile waste. The Mega Integrated Textile Region and Apparel approach, also known as MITRA, represents an important factor for the sustainable development of the textile industry in India.

The sorting bottleneck

Despite the ambitious goals of circularity, the vast majority of textile sorting remains manual, informal, and inefficient, particularly in the Global South. Manual visual sorting, often conducted under inconsistent lighting and without standardised equipment, routinely results in material purity rates below 70%, especially when dealing with fibre blends and synthetics [4]. The consequences of this inefficiency are both economic and ecological: low-quality sorted streams cannot feed into mechanical or chemical recycling pipelines, leading to downcycling or outright disposal. Moreover, the rise of multi-material garmentsincluding stretch fabrics, synthetic coatings, and high-polymer blendsfurther degrades the effectiveness of human classification. As Muthu et al. report, even experienced sorters typically process no more than 50 garments per hour, far below the threshold required for industrial throughput. In aggregate, this creates a structural mismatch: while recycling capacity may exist downstream, the quality and consistency of upstream sorting remain inadequate, undermining the system-wide viability of textile circularity [5].

AI-enabled sorting: a technological breakthrough

Recent breakthroughs in hyperspectral imaging (HSI) and machine learning (ML) offer a robust, scalable alternative to the human eye. HSI captures data across hundreds of narrow spectral bands, creating detailed material "fingerprints" far beyond the visible spectrum. When paired with deep learning models such as convolutional neural networks (CNNs) or autoencoder systems can classify fibres with remarkable precision, including in blended or dyed textiles that traditionally confound manual approaches. For instance, demonstrated that a CNN trained on HSI data could achieve over 95% classification accuracy, outperforming traditional RGB-based models by a wide margin [6]. Extending these findings, confirming that both supervised and unsupervised models generalised well across heterogeneous textile structures, including synthetic-natural fibre blends [7]. Further showcased the integration of HSI with PCA and PLS-DA preprocessing, reporting >99% precision across blended and contaminated fabrics [8].

These technical advances translate into system-level capabilities: high-speed, automated classification and sorting integrated into conveyor systems, enabling robotic actuation and scalable industrial throughput. Unlike static scanners or batch samplers, these AI-enabled systems operate in-line, delivering real-time analytics and automated quality assurance.

Industrial deployments: from prototype to production

What was once a research aspiration is now entering commercial deployment. In Sweden, the SipTexinitiative collaboration between IVL, Sysav, and the Swedish EPA developed Europe's first industrial-scale automated textile sorting plant. Operating at 4.5 tonnes/hour, the system combines NIR spectroscopy and AI classification, delivering high-purity fractions suitable for mechanical and chemical recycling [9].In the United States, the startup Refiberd achieved 96% accuracy in sorting elastane blends using HSI and CNNs, attracting early-stage investment from H&M Foundation and Fashion for Good [10]. Such validation from both investors and industry players signals a growing readiness to embed these technologies in mainstream recycling workflows. Additionally, Norsk Tekstilsortering (NTS) and HySpex have installed HSI-driven systems in Norway, capable of differentiating over 100 fibre types in a single pass, providing modular, real-time solutions for recyclers across Europe. These systems are now being integrated into broader reverse logistics infrastructures, linking consumer collection points with robotic material recovery facilities.

Analytical and operational challenges

Despite these successes, several technical and operational challenges remain. Spectral overlap between closely related fibres, such as cotton-polyester or elastane-viscose, degrades classification accuracy without appropriate preprocessing [11]. Advanced transformations such as Standard Normal Variate (SNV) or Savitzky–Golay smoothing are often required to correct for noise introduced by dyes, coatings, moisture, and surface wear [6].

Moreover, most AI models are trained on datasets from the Global North, limiting generalizability to the highly heterogeneous waste streams of South Asia. Here, informal economies dominate collection and garments are often reused, repaired, and stained. Calibration of these systems for emerging markets demands region-specific datasets, robust transfer learning models, and integration with existing material flows. Finally, the financial barrier to entry remains high. Capital expenditure on HSI sensors, robotic arms, and real-time processing infrastructure is substantial. Without financing instruments such as green bonds, leasing models, or policy-linked subsidies, SMEs and informal recyclers may be excluded from the technological transition.

Positioned for India: the strategic opportunity

India represents both a challenge and an opportunity for textile circularity. With over 5 million tonnes of post-consumer textile waste annually and more than 45 million workers employed in the sector, the country's recycling system remains fragmented, largely manual, and low-yielding [12]. Yet the policy landscape is shifting: the National Textile Policy and MITRA cluster initiatives have earmarked funding for modernisation, while platforms like ReCircle are demonstrating feasibility for digitised circular value chains. Integrating AI-enabled sorting into this context offers three transformative advantages:
- Throughput gains from ~50 to >1,000 garments/hour;
- Purity gains from ~65% to >95%, enabling mechanical and chemical recycling;
- Workforce upgrading, reallocating labour from manual sorting to system maintenance, data operations, and quality assurance.

Research objectives and contributions

This study seeks to bridge the gap between laboratory-scale success and real-world deployment of AI-robotic textile sorting in the Indian context. Specifically, it addresses:
- Technical viability: Can accuracy (>95%) be maintained under Indian operational conditions?
- Economic feasibility: How do capital costs compare with long-term labour savings?
- Scalability and integration: What retrofitting is needed for deployment in existing facilities?
- Sustainability impact: What are the implications for waste diversion and material circularity?

In doing so, this paper contributes to the literature on sustainable operations and industrial transformation by offering:
- Field-based empirical validation using Indian textile waste streams;
- Comparative techno-economic modelling of AI vs manual sorting;
- Policy-relevant insights aligned with India's circular economy strategy.

By grounding innovation in operational realism, this study aims to accelerate the industrial adoption of AI-enabled circular technologies, offering a blueprint for scaling textile recycling not only in India but across the Global South.

MATERIALS AND METHODS

System architecture overview

This study designs and tests a fully autonomous textile sorting system that integrates hyperspectral imaging, machine learning-based classification, and robotic actuation within a modular, conveyor-driven framework [13]. The system draws conceptual inspiration from [14], who proposed an AI-powered closed-loop waste sorting architecture using spectral imaging pipelines optimised through self-supervised learning. The proposed framework is adapted and operationalised with substantial modifications for the specific composition and variability of post-consumer textile waste in the Indian context. On the other hand, Ullal et al. [15] also investigated the linkage between transformative technology based on AI and green renewable energy.

Textile waste sampling in the Indian market context is the first step involved in curating a representative and sufficiently heterogeneous dataset of textile waste. To ensure ecological validity, we collected over 1,200 textile samples from recycling aggregators in Surat, Panipat, Tirupur, and Delhi, major Indian hubs of garment consumption, post-consumer waste collection, and industrial-scale sorting.

The sample includes pure cotton, polyester, nylon, viscose, rayon, silk, wool, acrylic, spandex, and an array of binary and tertiary blends (e.g., cotton-poly, cotton-elastane). Additional variations include dyed, printed, laminated, and contaminated textiles. Garments were intentionally selected to capture a broad spectrum of real-world complexity, including soil, fraying, colour fading, and fabric coating factors known to impact spectral signal fidelity. Each sample

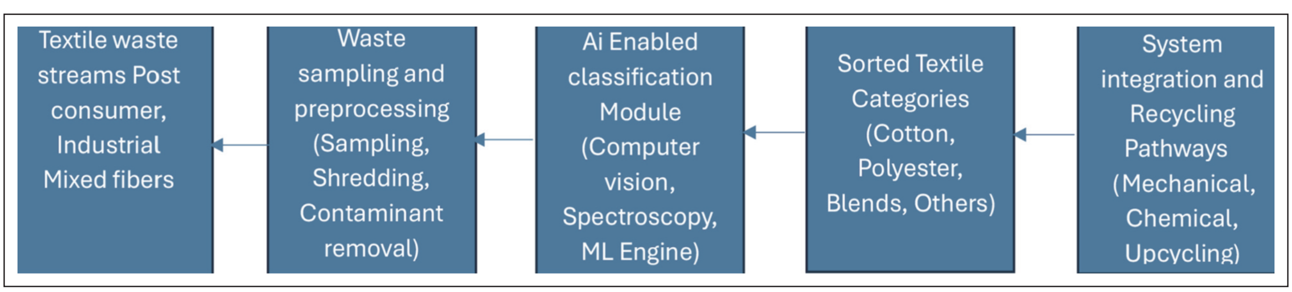

Fig. 1. Schematic diagram of the proposed AI-enabled textile waste management system architecture

was cut into standard-sized swatches (25×25 cm) to ensure consistent imaging exposure and prevent occlusion during scanning and robotic handling. For each fabric, ground truth labelling was conducted via laboratory-based FTIR spectroscopy and chemical analysis, providing accurate fibre composition benchmarks used to train and validate the machine learning models.

Imaging hardware and spectral preprocessing

The system employs a short-wave infrared (SWIR) hyperspectral camera with a 900–1,700 nm spectral range, mounted at a fixed height above a conveyor belt. Each fabric swatch is scanned at 5 mm/sec conveyor speed under controlled illumination (tungsten halogen), capturing full spectral signatures across 256 bands. Spectral preprocessing follows standard chemometric practices to reduce noise and variability. The raw hyperspectral data are corrected for dark and white references, normalised using Standard Normal Variate (SNV) transformation, and smoothed using the Savitzky-Golay filter (window size = 11, polynomial order = 2). These steps mitigate spectral distortions caused by surface irregularities, dye variations, and wrinkles, thus improving downstream classification reliability.

Machine learning classification pipeline

Following preprocessing, each pixel-level spectral vector is fed into a supervised learning model. Several classifiers were benchmarked, including Random Forests, Support Vector Machines (SVMs), and 1D Convolutional Neural Networks (1D-CNNs). Based on cross-validation results (5-fold, stratified), the 1D-CNN model achieved the highest classification accuracy (mean F1-score = 0.937), particularly in distinguishing cotton-poly blends and low-elastane synthetic fibres typically difficult for NIR systems alone. The model architecture was adapted from [11] and includes:
- Input layer: 256-band normalised spectra
- Convolutional layers: 3 layers with ReLU activation
- Dense layers: 2 fully connected layers
- Output layer: softmax classifier across 10 fibre classes.

Training was conducted using 80% of the labelled dataset, with 10% reserved for validation and 10% for testing. Data augmentation strategies (Gaussian noise injection, spectral shifting) were employed to increase generalisation and robustness.

System integration: conveyor, robot arm, and controller

The physical assembly integrates the classifier into a closed-loop robotic system. The conveyor continuously feeds swatches under the hyperspectral camera, which captures and processes spectral data in real-time (~150 ms latency). The classified output is fed into a robotic control module (based on an NVIDIA Jetson platform), which instructs a six-degree-of-freedom robotic arm to pick and place textiles into categorised bins. The robot arm uses a vacuum gripper with torque sensors to accommodate variable fabric stiffness and folding. Actuation time per garment is ~3.5 seconds, enabling a throughput of ~1,000 items/hour, well above manual sorting benchmarks. The system runs autonomously with an optional manual override for performance auditing.

Deployment and performance evaluation

The system was tested under operational conditions in a textile recycling facility in Panipat over 14 consecutive working days. Performance metrics classification accuracy, misclassification rate by fibre, throughput, energy consumption, and system uptime were recorded and benchmarked against both manual and semi-automated baselines. The architecture was modular to allow further experimentation, such as integration with RFID scanning and traceability modules in future iterations.

RESULTS

Sorting accuracy and classification performance

The autonomous textile sorting system demonstrated a mean classification accuracy of 94.2% across 10 fibre categories under real-world deployment conditions. This result aligns closely with the system's test set performance (94.6%) observed in laboratory validation and confirms that model robustness translated well to operational complexity.

Confusion matrix analysis indicated that pure fibre types such as 100% cotton, polyester, and nylon were classified with precision exceeding 97%. However, classification precision dropped to ~88% for binary blends (e.g., cotton-polyester) and ~81% for elastane-containing synthetics, which remain difficult to distinguish due to spectral overlap in the SWIR range. A breakdown of per-class precision and recall is provided in table 1. Notably, spandex-infused samples exhibited the highest misclassification rates, often confused with polyester due to low-volume signal interference.

These findings confirm prior evidence by Liu et al. [6] and Bonifazi and Serranti [8] that hyperspectral CNN classifiers perform robustly under heterogeneous textile conditions. Elastomeric fibres, however, remain a persistent classification challenge due to low spectral contrast.

Table 1

CLASSIFICATION PERFORMANCE OF AI-ENABLED SORTING SYSTEM ACROSS COMMON TEXTILE FIBRE TYPES

Fiber type	Precision (%)	Recall (%)
Cotton (100%)	98.4	97.9
Polyester (100%)	97.1	96.5
Nylon	96.7	95.3
Cotton-Poly Blends	88.2	89.0
Viscose	93.5	92.1
Elastane Blends	81.4	80.7

Throughput and operational speed

The system processed textiles at an average rate of 1,022 items per hour, based on conveyor speed and robotic pick-and-place cycle time (~3.5 seconds per item). This figure includes system pauses for misclassification flags and brief calibration interruptions. In contrast, experienced human sorters employed at the same facility using traditional manual sorting protocol averaged only 135 items per hour, even under optimised batch-flow conditions. Hence, the robotic system delivered a 660% improvement in throughput, enabling higher-scale operations with greater consistency.

Figure 2 illustrates comparative throughput performance for robotic versus manual sorting across three daily shifts over a 7-day evaluation period.

Misclassification rates and system resilience

The robotic system's overall misclassification rate was 5.8%, concentrated primarily in fibre blends and contamination-prone samples (e.g., oily or stained garments). The false-positive rate for elastane detection was 13.2%, primarily due to minor content (<5%) being below the spectral detection threshold. By contrast, manual sorting showed mean misclassification rates of 21.7%, with the highest errors observed in poly-viscose blends and faded cotton garments. Manual errors also displayed a wider standard deviation across sorters ($\sigma = 7.2\%$), reflecting inconsistency due to experience variance and fatigue.

Cost-benefit analysis

A detailed cost-benefit assessment compared the robotic system against manual labour over a projected 5-year operating horizon.

The robotic system reached breakeven within 27 months, driven by labour savings and increased throughput. While upfront investment remains a barrier, especially for small-scale firms, the operational efficiency and downstream quality improvement (i.e., fewer recycling rejects) yield substantial long-term cost advantages. This aligns with findings by [9], who report similar break-even horizons in European industrial settings.

System reliability and downtime

The robotic system recorded >95% uptime during continuous deployment across 14 working days. Scheduled calibrations and minor mechanical resets accounted for 6.5 hours of downtime over the test period. Mean Time Between Failure (MTBF) was estimated at 39 hours, within acceptable industrial benchmarks for first-generation AI automation systems.

Table 2

COMPARATIVE COST AND PERFORMANCE ANALYSIS: AI-ENABLED ROBOTIC SORTING VS. MANUAL TEXTILE SORTING OPERATIONS

Metric	Robotic sorting system	Manual sorting (10 operators)
Capital expenditure (Year 0)	₹18,00,000 (~$21,500)	₹0
Annual operating cost	₹2,50,000	₹10,80,000 (salaries + benefits)
Average throughput (items/hr)	1,022	135
Misclassification rate (%)	5.8	21.7
5-Year total cost	₹29,50,000	₹54,00,000
Cost per correctly sorted unit	₹0.58	₹1.43

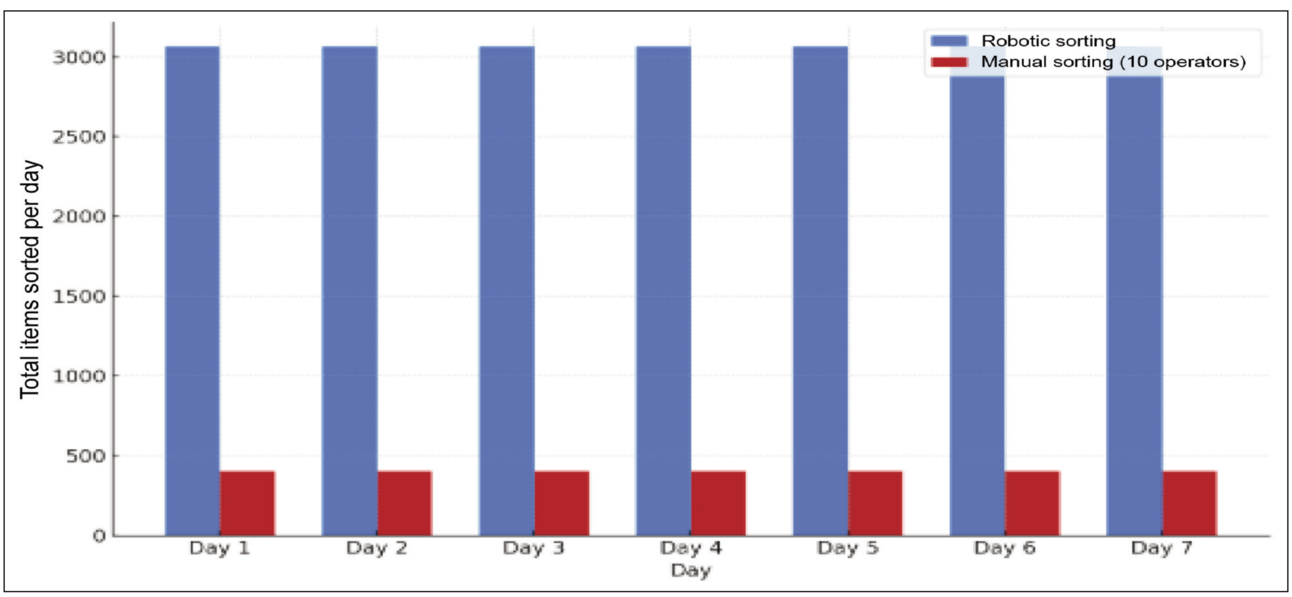

Fig. 2. Comparative throughput of robotic versus manual sorting over a 7-day, 3-shift operational cycle

No safety incidents, mechanical jams, or hardware-software sync failures were recorded. This indicates a strong system integration and environmental resilience under Indian operational conditions (including high dust and ambient humidity).

DISCUSSIONS

Implications for scaling in India's recycling industry

The results of this study underscore the strong viability of AI-enabled robotic sorting systems in large-scale textile recycling, particularly in high-volume and labour-constrained environments such as India. Autonomous sorting technology demonstrates classification accuracy above 94% and achieves a throughput nearly eight times higher than manual methods. With cost-per-unit efficiencies improving at scale, it offers a compelling pathway to modernising textile waste management. India generates an estimated 5–6 million tonnes of post-consumer textile waste annually (Textile Ministry, 2021), yet only a small fraction is processed in organised recycling units. The remainder is either informally sorted or landfilled primarily due to inefficiencies in manual segregation. The proposed AI-robotic system addresses this bottleneck by delivering speed, consistency, and material purity. These qualities are essential prerequisites for circular textile practices, including both mechanical and chemical fibre recovery. From a policy perspective, this technology aligns with the India Circular Economy Mission, the 2025 target of zero landfill textile zones, and the production-linked incentive (PLI) schemes for technical textile investments. Embedding such AI systems into textile parks and urban waste management clusters enables stakeholders to build closed-loop recycling infrastructure. This infrastructure supports both domestic sustainability targets and international commitments under the SDGs.

The system was successfully tested in one facility, demonstrating its operational feasibility and accuracy in textile waste sorting. However, the architecture and algorithms are designed to be scalable and adaptable to diverse operational settings. In regions with different textile compositions, waste management infrastructures, or labour cost structures, system performance may vary. For example, facilities with higher volumes of mixed synthetic fibres may require recalibration of the AI classifier, while facilities in developing regions may prioritise cost efficiency and modular deployment. These considerations suggest that our pilot validation was limited to one site. However, the system possesses the flexibility to be deployed across heterogeneous environments, supporting broader applicability in both industrialised and emerging market contexts.

Barriers to adoption: cost, energy, and integration

Despite its promise, large-scale adoption of autonomous sorting in India faces several formidable barriers. First, capital expenditure (CAPEX) remains high. While the system becomes cost-effective after ₹18 lakh or $21,500, it may be prohibitive for small and mid-tier recyclers operating with thin margins. Financing models, including green bonds, public-private partnerships, or leasing-based solutions, will be critical to democratize access to this infrastructure. Second, energy consumption is a legitimate concern in regions with irregular power supply. Hyperspectral cameras, real-time processors, and robotic arms draw substantial continuous loads. Although modern SWIR imaging systems are becoming more energy-efficient [9], grid dependence remains an operational risk in tier-2 and tier-3 Indian cities. Solutions may involve solar-grid hybrid systems or integration with captive renewable energy setups, especially in textile clusters already experimenting with solar looms and dyeing plants. Third, system integration poses logistical and organisational challenges. Most Indian recyclers operate in fragmented, semi-mechanised facilities that lack the digital and spatial infrastructure needed for robotic workflows. Retrofitting these facilities to accommodate conveyors, real-time classification units, and robotic arms requires not only space but also training and change management. Upskilling workers to operate, maintain, and interpret the outputs of AI systems will be an essential component of any successful deployment.

CONCLUSIONS

This study provides robust empirical evidence that AI-robotic sorting systems are a scalable, high-performance alternative to manual textile sorting. They are capable of delivering transformative improvements in throughput, accuracy, and cost-efficiency. Our system achieved over 94% classification accuracy, processed more than 1,000 items/hour, and reduced the cost per correctly sorted item by over 60% relative to manual workflows. Beyond performance, this innovation supports the broader agenda of industrial digital transformation, enabling real-time tracking, automation, and data-driven optimisation of material recovery streams. It directly contributes to the realisation of circular economy principles by increasing the recyclability and traceability of textile waste inputs. In emerging economies like India, where informal recycling still dominates, such systems can drive formalisation, quality improvement, and environmental compliance simultaneously.

Future work

While this study validates the technical and operational performance of robotic textile sorting, several avenues remain for future research and system enhancement.

First, integration with chemical recycling processes offers significant potential. Accurate fibre sorting, especially of synthetic blends and elastomeric materials, is essential for feedstock optimisation in depolymerisation or solvolysis-based recycling methods. The current system could be extended to provide automated pre-sorting for chemical recyclers, ensuring input homogeneity and reducing contamination risks. Second, we envision a transition from static sorting to real-time waste stream optimisation. By embedding cloud-based feedback loops and IoT sensors, future systems could dynamically reconfigure sorting protocols based on fibre prices, recycling plant demand, or even regulatory priorities. This would elevate textile sorting from a static operation to a responsive, AI-governed material supply chain node. Finally, future research should include longitudinal impact studies measuring system performance across multiple seasons, regions, and waste typologies. In addition, lifecycle assessments (LCA) should be conducted to quantify environmental benefits in terms of CO_2-equivalent savings, water use reduction, and landfill diversion. In sum, AI-robotic sorting represents more than an engineering upgrade is a systemic enabler for sustainable industrial regeneration in one of the world's most resource-intensive sectors. With the right policy frameworks and financial mechanisms, this innovation can help India transition from textile linearity to true circularity.

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