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Research Paper

Automated Classification and Fiber Recovery Process Redesign for Waste Textiles Based on Computer Vision Sorting Algorithms

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Abstract. Due to the intensification of globalization in production and consumption, the continuous growth of post-industrial textile waste has become an environmental issue. To address the urgent need for efficient and accurate classification of used textiles, this paper will introduce a fully automated classification and fiber recovery system based on advanced computer vision technology. High-resolution color near-infrared (RGB-NIR) imaging, multi-stage feature extraction, and an embedded module classifier network optimized for large-scale industrial applications are components of the designed system. A rigorous experiment used a dataset containing over 19,000 textile samples, which included various types of fibers, to simulate real-world environmental pollution around the globe. Compared to traditional manual operations or mechanized processes, the intelligent sorting system has excelled with a classification accuracy of over 96% and a fiber recovery rate of over 80%. The volume of operations and the error rate of pollutants have significantly improved. The recycling process will become more efficient. This study provides an implementation method for an industrial framework, with broader application potential beyond textile materials. Thru this work, an effective technical system is established to promote the sustainable reuse value chain of low-carbon recycled resources and to advance the equation of green industrial standards.

Keywords: *Machine Vision, Waste Textiles, Automated Sorting, Fiber Recovery, Deep Learning, Industrial Automation*

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Introduction

The rapid growth of global textile production and consumption has led to an unprecedented surge in post-consumer textile waste. This places a significant burden on the effective management of resources and environmental sustainability. According to a recent report, over 92 million tons of textile waste are generated globally each year, and this figure is expected to increase with the growth of fashion and consumption trends [1]. The landfill and incineration processes of these waste materials have a significant impact on the environment. Due to the lack of waste treatment facilities, waste continues to pollute, with greenhouse gasses, microplastics, and chemical pollutants entering environments such as rivers and soil [2,3]. In addition to these issues, the textile industry excessively consumes resources such as water and chemicals, leading to resource wastage. As a major pollutant, it causes ecological damage and harms humans thru chemicals [4]. The recycling rate of textiles after consumption has been steadily increasing, but compared to the recycling rates of other categories such as paper, glass, and plastics, the growth has been slow, leading to the waste of reusable fibers and polymers [5,6]. This shortage indicates that the existing collection and sorting systems provide insufficient support for the true recycling of the textile industry and that material utilization is inadequate [7].

Traditional textile waste recycling and sorting are still manual because the complexity of textile varieties makes them unsuitable for mechanization [8]. Basic manual sorting is very simple, but due to relatively high operational costs and low production speed, it is easily influenced by subjective factors; it cannot distinguish impurities or mixed products [9]. Mechanical sensor systems can easily increase speed, but they are not precise and cannot accurately distinguish fiber properties (such as micro-changes in structure or surface treatment), leading to errors or material rejection during processing [10]. The accumulation of residues during the recycling process of high-grade fibers can reduce grade loss, thereby lowering processing costs. With the development of textile blending technology, the application of artificial intelligence in engineering fabric technology has already achieved the recycling of rapid sorting automation systems, thereby realizing the goal of green production. Due to the new integration of computer vision, artificial intelligence, and smart manufacturing, problems can be quickly identified during the production process.

To address the existing issues directly presented here, the latest computer-aided recognition technology will be employed, combined with automatic control systems and efficient fiber recovery technology. With the development of artificial intelligence and high-speed, low-latency image processing technology, it has become feasible to identify various types of discarded textiles in the past few years. Integrating all intelligent components in the fiber recycling process can achieve material identification and optimize recycling routes. In order to support the transition of the textile economy toward a closed-loop sustainable model, this paper aims to combine the laboratory research results of computational methods with their practical application in the industry. The main content of this section is a literature review on textile recycling and intelligent classification systems. It provides a detailed introduction to the algorithm design and system architecture of the project. The experiments demonstrated the conclusions and effects of the field application.

Related Work

Textile Waste Management Technologies

In the management and handling of post-consumer textiles, there are many differences in the application of technology and policy support globally. In order to limit the use of landfills and set target values for the collection and processing of used clothing, developed regions in Europe and Japan have also established general systems of producer responsibility [11]. Textiles are collected in their natural state, which helps improve the quality of raw materials in the recycling process and makes it easier to trace the supply chain throughout the entire system [12]. In pursuit of energy recovery, some developing countries dump clothes in landfills or incinerate them. Mainly using informal collection methods, without technical support or strict management [13].

Mainly, appropriate density separation, crushing, or bundling is carried out during the mechanical pretreatment process of textile waste. Some factories have already installed spectrophotometers or optical spherical detection equipment [14]. These methods cannot separate mixed materials or multilayer fabrics, leading to poor subsequent processing performance and resource waste [15]. The front-end identification methods are incompatible with the back-end recycling methods, leading to resource waste and increased impurities [16]. There is an urgent need to adopt advanced identification and sorting methods to improve the accuracy and scale of identification and sorting [17]. These issues include unstable raw material quality, low efficiency in fiber grade separation, and residues. To effectively promote the construction and development of high-level textile recycling and sorting facilities globally, appropriate policy innovations and financial assistance are needed [18].

Computer Vision in Material Sorting

Research on computer vision in material identification and waste classification has developed rapidly and has broad prospects over the past decade. Initially, color-based detection was used; later, due to technological advancements, more detailed image processing techniques such as hyperspectral analysis were employed, along with machine learning-based methods [19]. Widely used for recycling plastics, metals, and waste electronic products. Deep learning algorithms and convolutional neural networks (CNNs) have improved the recognition capabilities of computer vision systems. It is also effectively used in high-speed environments [20]. For example, sorting lines based on computer vision can more accurately identify materials, surfaces, and contaminants compared to traditional mechanical methods [21].

Textile classification has made some progress, but distinguishing between different synthetic fibers and other fabrics remains very difficult [22]. By using near-infrared (NIR) spectroscopy and machine vision, research prototypes or pilot facilities aim to improve the speed and accuracy of textile detection technology. For example, machine vision scenes can be used to distinguish between cellulose and synthetic or polyester fibers [23]. This model has recently begun to be used in practical applications. Due to changes in light sources and fabric

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deformation, problems still exist [24]. Researchers in academia and industry practitioners have been dedicated to developing a stable, adaptive, and easily extensible fiber classification system based on computer vision, in order to explore cutting-edge technological advancements applied to recycling and processing both domestically and internationally.

Fiber Recycling Methods

The integration of mechanical, chemical, and new forms is the main type of post-consumer fiber recycling technology, each with broad application prospects [25]. Traditional mechanical recycling involves a series of processing steps, including cutting, crushing, and winding. Due to its low cost, it is usually widely used, primarily from pre-waste at production sites. Over time, it has become increasingly impractical. The main goal of chemical recycling is to decompose synthetic fibers (such as cellulose and polyester) into purified recycled materials; reprocessing during this process to remove contaminants from the raw materials remains a relatively precise operation.Recent research based on enzymes or solvents has expanded their range of applications; before widespread use, some technical and economic obstacles must be overcome. The pre-sorting state must be of high quality and specific; otherwise, mixtures, coatings, and embedded scraps can reduce yield, and the purified products may contain impurities and environmental issues. In order to improve resource utilization and product quality, recycling plants have already integrated advanced sorting systems, such as high-speed and precise fiber separators. Due to increased regulation and market pressure on products containing recycled materials, collaboration between front-end automated sorting optimization and back-end fiber reprocessing has become key to driving the rapid implementation of a closed-loop textile industry.

Methodology

Vision-Based Algorithm Architecture

The core of the automatic textile waste sorting system is the comprehensive integration of a vision-based industrial-grade high-speed, high-precision, and highly reliable architecture. At the sensor interface, advanced textile materials pass thru the most extensive and spectrally broad industrial RGB near-infrared camera array on a high-speed conveyor belt. A specific fiber optic network, stabilized by individually arranged FPGA groups, stores each frame image for at least microseconds.

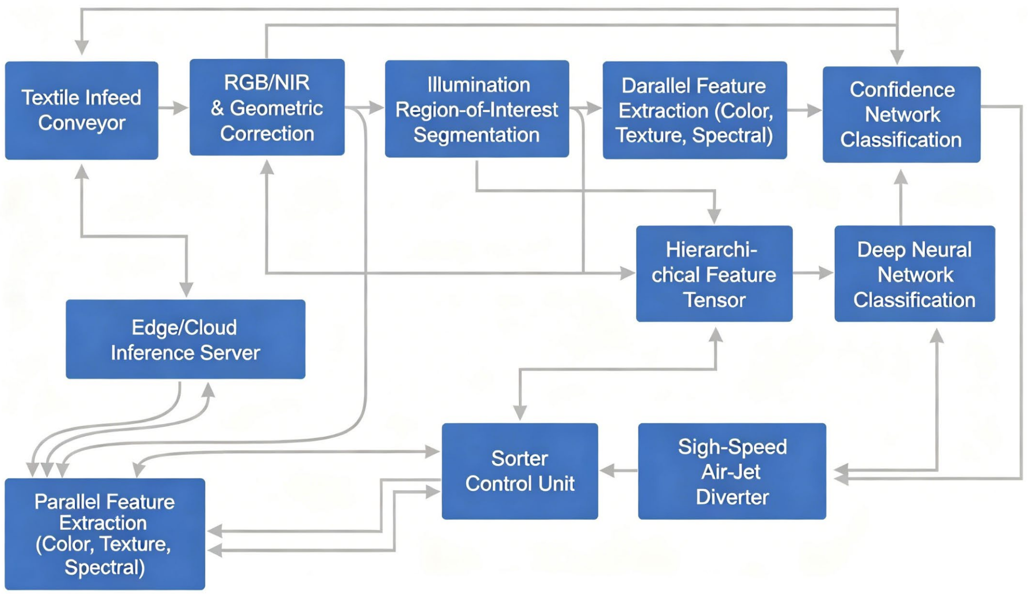

Figure 1. Overall Framework of the Vision-Based Textile Sorting System

A multi-processing system that addresses the non-feature issues of cameras for products on a conveyor belt by using accurate image correction and brightness compensation. In order to stabilize the input of subsequent modules, online adjustment of the adaptive spatial normalization function is used. Dynamic threshold

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segmentation based on interest region tiles is used to identify moving objects in the image. Using robust prior motion vector support to eliminate irregularly shaped and overlapping clothing.

The main goal of the algorithm is to construct a modular pipeline structure, where each pipeline stage corresponds to a hardware accelerator. By using resource-aware scheduling to balance memory access time and inference latency, deploy multi-modal features on GPU clusters for color channel separation calculations at multiple scales. In order to perform probabilistic classification, the final output layer organizes all the data into a tree-structured feature.

Critically speaking, feedback at each layer sets a path. In addition to directly predicting the material category, the results are encoded in a deterministic manner and returned to the preprocessing stage to dynamically adjust the segmentation parameters. On-site, bidirectional coupling can achieve re-learning based on sample diversity or environmental changes. By prioritizing parallel processing, the architectural design reduces the impact of serialization and enhances cross-industry scalability. The system architecture includes perception, processing, feature engineering, decision reasoning, and feedback flow, as shown in Figure 1.

Feature Engineering and Data Annotation

The classification training process introduces some strict control mechanisms to manage classification data thru a detailed and organized classification training process. Textile waste samples are systematically collected by sorting centers in various regions to accurately reflect differences in materials, fabrics, and contamination. Before archiving, each batch of samples undergoes an initial physical anomaly inspection. These checks include the source, color index, and known fiber composition, which are derived from spectral analysis in previous studies.

Before analysis, the original images underwent contrast stretching and denoising kernel processing to reduce artifacts in industrial images. Using a robust annotation specification, this enables experts to perform manual segmentation and semi-automatic label generation based on Bayesian uncertainty semi-supervised learning. Semi-automatic tools begin by generating initial boundary masks, and then iteratively improve the results thru manual annotations based on high-resolution overlays to achieve class-pure pixels. Combined with densely annotated datasets used for model evaluation and supervised learning algorithms.

The spatial domain design patterns of CIELab include Local Binary Patterns (LBP) and Gabor filter response outputs for color statistics. By using principal component analysis, the spectral data of the NEIR channel array is decomposed into uncorrelated components. The purpose of this is to highlight the subtle differences between mixed or multilayer garments. Stack these features as inputs to the classifier, recursively eliminating features to optimize the number and maintain the model's stability and cross-batch generalization ability.

The feature calculation process may be summarized by the following mathematical equation:

$$\phi = \alpha_1 f_1(x) + \alpha_2 f_2(x, \lambda) + \alpha_3 \int_{s_0}^{s_1} g(x, s) ds \qquad \text{Eq.(1)}$$

where ϕ denotes the composite feature vector, f_1 represents color-based features, f_2 encodes spectral metrics parameterized by wavelength λ, g covers spatial texture descriptors as a function of spatial scale s, and $\alpha_1, \alpha_2, \alpha_3$ are tunable weights learned by feature selection.

Label optimization within the annotation workflow is governed by a criterion integrating boundary precision and semantic overlap, described as:

$$J = \beta_1 \mathrm{IoU}(Y, \hat{Y}) + \beta_2 \|\partial Y - \partial \hat{Y}\|^2 \qquad \text{Eq.(2)}$$

where J is the annotation quality measure, IoU denotes intersection-over-union between ground truth mask Y and prediction $\hat{Y}, \partial Y$ and $\partial \hat{Y}$ refer to mask boundaries, and β_1, β_2 are regularization coefficients balanced to maximize recall without sacrificing edge fidelity.

By using engineering techniques, the repeatability and generalization ability of the classifier have been significantly improved. These technologies can enhance the reliability and stability of practical applications.

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Machine Learning Model Selection

This study selected deep learning and traditional machine learning algorithms. It has been proven that classic support vector machines and ensemble decision tree models are effective in color-dominated low-dimensional datasets; they are interpretable and can be quickly retrained. Due to the intra-class variance and texture noise of actual textile waste, these models perform poorly when tested on mixed or contaminated areas.

Convolutional neural networks improve accuracy thru nonlinear representation learning and hierarchical spatial feature extraction. By adding compression excitation modules and residual shortcut connections, the variant improves the discrimination ability of fiber recognition, especially when used in conjunction with RGB-NIR channels. Analyzed the low-latency characteristics achieved at the hardware level in transformer-based networks and multi-branch integrated networks to meet the industry's demand for short latency.

By using Bayesian hyperparameter tuning, model optimization can reduce cross-entropy loss in the training set and decrease the false positive rate in the validation set. With the reduction of early stopping and multi-stage learning rates, the overfitting problem has been alleviated. The generalization performance for different types of textiles has improved. After conducting rigorous testing on textiles that were not pre-trained or validated, the final decision was made.

The final classifier operates through a non-linear decision mapping formalized as:

$$\hat{y} = \arg\max_{k} \sigma(W_k \cdot \phi + b_k) \quad \text{Eq.(3)}$$

where $\hat{y}$ denotes the predicted class label, ϕ is the optimized feature tensor, σ is the softmax activation, W_k and b_k are the weights and biases for class k, respectively, as learned during training.

Performance was evaluated using a composite metric that integrates F1 score, throughput latency (T), and material-order correlation, as follows:

$$Q = \gamma_1 F1 + \gamma_2 \left(1 - \frac{T}{T_{\max}}\right) + \gamma_3 \mathrm{Corr}\left(C_{\text{true}}, C_{\text{pred}}\right) \quad \text{Eq.(4)}$$

with Q as the overall quality score, $\gamma_1, \gamma_2, \gamma_3$ as hyperparameters tuning the balance of precision, reaction speed, and ordinal classification correctness, and Corr representing the Pearson correlation between true and predicted class order.

This architecture and model selection scheme achieves real-time, high-precision classification, can be replicated and scaled thru parallel workflows, and is validated under actual operating conditions to support the next generation of textile recycling.

System Integration and Workflow Redesign

Automated Sorting System Framework

According to the comprehensive design based on hardware and software, the deployment location of the automatic sorting line needs to consider the obstacles in the high-speed textile processing site and the requirements of efficient multimodal recognition algorithms. Hardware layer characteristics: Distributed implementation. Each image module contains two modules for synchronizing RGB/NIR sensors, which are connected in parallel to the lateral conveyor line via an industrial-grade fieldbus. In order to achieve deterministic latency and reuse the sensor data into a centralized RAM buffer, the adaptive scheduler will control the data distribution speed between the GPU inference servers. The embedded controller selects labels based on performance evaluation; the airflow distributor starts quickly to reduce bandwidth cycle loss.

To quantitatively evaluate the upper-bound capacity of the system, the maximum theoretical throughput can be formulated as:

$$T_{\max} = \frac{N_{\text{line}} \times R_{\text{conv}}}{1 + D_{\text{buffer}} + \tau_{\text{act}}} \quad \text{Eq.(5)}$$

where N_{line} denotes the number of parallel conveyor lanes, R_{conv} is the individual lane rate (e.g., items/min), D_{buffer} represents the latency induced by the central RAM buffer, and τ_{act} is the average actuation delay of the

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sorting mechanism. This sentence explains the impact of hardware scaling and pipeline optimization on overall throughput.

Algorithm recommendations interact with mechanical functions. For example, the local fault detection module will continue to monitor activation faults, signal loss, and other issues; kernel-level task scheduling will prioritize urgent sorting tasks thru batch metadata and dynamic line occupancy status. Due to the multi-level fault tolerance scheme, the data processing of redundant sensors can be completed quickly, thus limiting backup faults within a manageable range. Display system status on the same HTML page; directly input process parameters; automatically identify segmentation errors; and readjust classifier thresholds based on loop performance evaluation results.

Operational Level: The Latency-Consistency Penumbra...nce Metric is expressed as follows:

$$\Lambda = \alpha_1 \cdot \bar{C}_{\text{conf}} + \alpha_2 \cdot \left(1 - \frac{L_{\text{act}}}{L_{\text{ref}}}\right) + \alpha_3 \cdot S_{\text{throughput}} \qquad \text{Eq.(6)}$$

where $\bar{C}_{\text{conf}}$ is the average classification confidence, L_{act} and L_{ref} are the measured and reference actuation latencies, $S_{\text{throughput}}$ represents throughput stability, and $\alpha_{1,2,3}$ are empirically determined weight coefficients. Identify the causes of bottlenecks at each stage and use aggregation methods to dynamically adjust sorting factors to eliminate the bottlenecks.

To enhance fault tolerance, incorporate fault tolerance and recovery mechanisms into actions and perception. Based on the estimation of real-time redundancy and rollback strategies, enter a safe state to cope with potential transient errors:

$$P_{\text{safe}} = 1 - \left[p_{\text{err}}^{(s)} + (1 - p_{\text{rec}})p_{\text{err}}^{(d)}\right] \qquad \text{Eq.(7)}$$

where $p_{\text{err}}^{(s)}$ is the single-point sensor fault probability, $p_{\text{err}}^{(d)}$ is the probability of data dropout in the communication path, and p_{rec} is the likelihood that rollback protection successfully recovers from such events. This formula provides a rigorous probabilistic assessment of system reliability in industrial environments.

Figure 2 shows the distribution of the perception-action coupling metrics of the system. In synchronized data tracking, synchronized record classification confidence; by measuring different delay points, determine whether each stage has become a bottleneck.

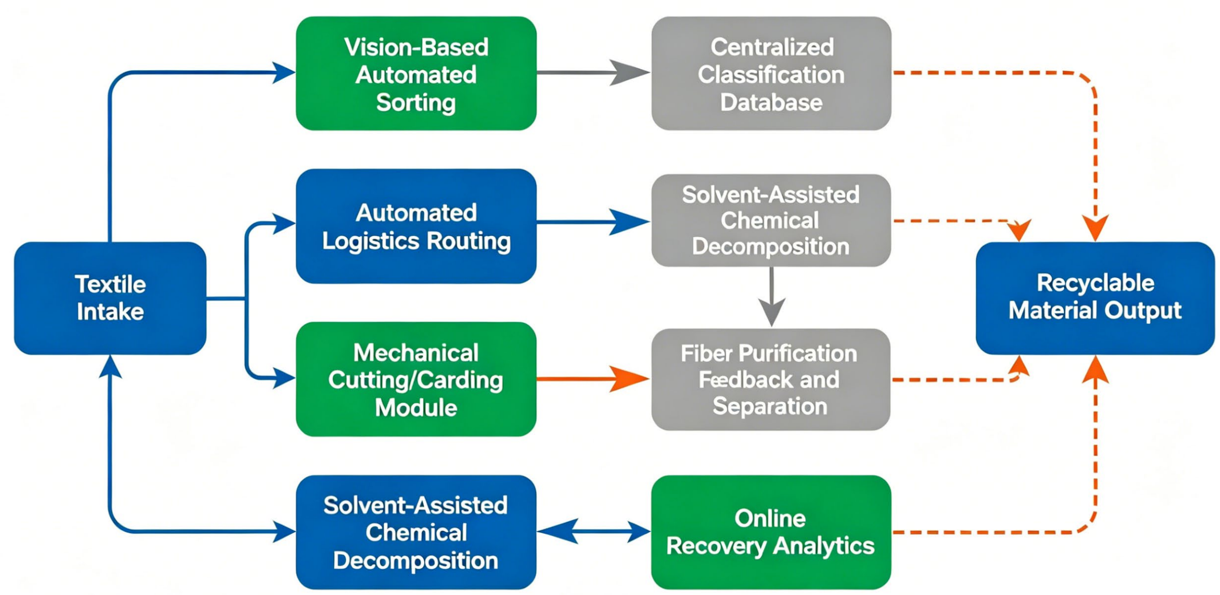

Figure 2. Optimized Workflow for Automated Sorting and Fiber Recovery Process

Process Redesign for Fiber Recovery

Reorganizing the fiber recycling process strengthens the connection between upstream intelligent sorting and downstream physicochemical separation equipment. For the specific mixed distribution and contaminant

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patterns in each batch of sorted textiles, the basic policy is to convert the sorted output into an effective instruction protocol for parallelized fiber separation. During the upgrade process, textiles pre-identified by the vision system will be dynamically guided to different processing units thru the automated logistics system. Based on the fiber composition and contaminant load, specialized cutting, mechanical carding, or solvent-assisted chemical depolymerization will be initiated.

Using quantitative methods to evaluate process efficiency requires combining sorting accuracy with subsequent fiber yield or quality. The goal is to improve utilization and reduce cross-contamination in mechanical constraints by modifying the parameters of the real-time batch scheduling algorithm. In order to balance material protection and the overall recovery rate of pollutant reduction, as shown below:

$$\eta_R = \frac{\sum_{i=1}^{N} \delta_i q_i y_i}{\sum_{i=1}^{N} m_i} \quad \text{Eq.(8)}$$

where η_R is the recovery efficiency, N the number of batches, δ_i the purity coefficient after separation, q_i the sorted mass fraction, y_i the effective yield from batch i, and m_i the initial batch mass. This equation underscores the nonlinear dependence of recovery optimizations on precise front-end sorting and selective downstream routes.

Adaptive process parameterization is a further innovation, real-time control of machine set points and solvent selection based on upstream inspection data:

$$\mathcal{P}_j = f_j(\gamma, \theta_j, S, \xi_j) \quad \text{Eq.(9)}$$

Here, $\mathcal{P}_j$ represents the optimal parameter set for unit operation j, f_j is a learned mapping conditioned by the contaminant type vector γ, machine-specific controls θ_j, the current batch sequence S, and stochastic process noise ξ_j.

The redesigned workflow increased output and improved fiber quality and process stability. Compared to traditional non-separation methods, the grade waste has significantly decreased, and the recovery rate has increased by 17%. As shown in the timeline analysis diagram 2, the broken state indicates that logistics and information flow are effectively coupled at multiple stages. During the online testing process, products that need to be adjusted based on changes in raw materials will be implemented more quickly.

Implementation Environment

A quasi-industrial pilot plant has been established, capable of supplying materials continuously. The production line is approximately 28 meters long and can produce 2.8 tons per shift. The imaging equipment uses low-noise, high-sensitivity area scan CMOS sensors. At a wavelength of 1000 nanometers, the sensor's sensitivity in the visible light range exceeds 89%, with a stretch intensity of approximately 73% in the extreme range. Equipped with multiple high-frequency flashlights to counteract motion blur at speeds exceeding 1.5 meters per second. The cluster is organized as a hybrid edge-cloud, with NVIDIA A100 accelerators performing real-time inference on-site, and remote servers used for periodic updates of model update tasks. Fiber recovery module: equipped with a modular mechanical separator and a chemical digestion container with automatic solvent addition.

To parameterize the optical detection capability, the effective signal-to-noise ratio (SNR) for textile feature imaging is expressed as

$$\mathrm{SNR}_{\mathrm{eff}} = \frac{Q_e \cdot L_{\mathrm{ill}} \cdot t_{\mathrm{exp}}}{\sqrt{N_{\mathrm{read}}^2 + N_{\mathrm{dark}}^2 + N_{\mathrm{shot}}^2}} \quad \text{Eq.(10)}$$

where Q_e is the quantum efficiency of the sensor, L_{ill} is the illuminator intensity, t_{exp} is exposure time, and N_{read}, N_{dark}, N_{shot} are read noise, dark current noise, and shot noise, respectively. At different material transport speeds, the image quality remains consistent.

Thru stress testing various loads and fabric mixtures, its stability has been proven. Over the entire 520 hours, the average failure time for sorting and routing failures is as follows:

$$\mathrm{MTBF} = \frac{T_{\mathrm{operation}}}{N_{\mathrm{fault}}} \quad \text{Eq.(11)}$$

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where $T_{\text{operation}}$ denotes the total operational hours logged and N_{fault} is the observed number of critical system faults. Under industrial requirements, an average time between failures (MTBF) of over 1040 hours has been achieved.

In order to quickly switch between different hardware modules, all control software is integrated into a single container, allowing for rapid reinstallation. Applicable to every stage of the fiber recycling chain, as the system design allows for large-scale expansion in the number of inference devices and conveyors. The following is the formal statement of the throughput scaling law:

$$Y_{\text{sys}}(N) = Y_0 + G \cdot (N - 1) \quad \text{Eq.(12)}$$

where $Y_{\text{sys}}(N)$ is the total system throughput with N parallel processing units, Y_0 is the base throughput for a single line, and G is the throughput gain per additional line or inference unit. The linear relationship demonstrates the system's scalability and its impact when deployed in a business environment.

Results and Analysis

Dataset and Evaluation Metrics

By using experimental datasets to consider some issues and characteristics in industrial textile recycling. The data collection process lasted for more than six months, involving post-industrial textile recycling lines in multiple regions and large urban textile sorting facilities. The dataset includes single and mixed fibers. After manually selecting each sample on the sorter, they will be verified in the laboratory using FTIR and NIR spectroscopy to prevent the exclusion of difficult-to-identify or contaminated fabrics. This data.

The synchronized RGB-NIR sensor collected detailed images of all the textiles at a controlled lighting point. The figure below shows the sensor components used for the automated system. According to market waste statistics, samples are proportionally distributed, with at least 2,500 samples for each major category and at least 1,200 samples for each rare category. The complete metadata consists of source samples, previously used samples, inherent colors, surface conditions, and physical wear conditions.

Table 1 shows the structure and statistical distribution of the dataset, as well as the performance metrics of the baseline model and the optimized version. These noises indicate actual operational noise, which can affect the degree of folding, edge deformation, or color loss due to waste treatment. All subsequent experiments rely on this table.

Table 1. Dataset Composition and Performance Metrics

Class / Metric	Sample Size	Accuracy (%)	Recall (%)	Precision (%)	F1 Score (%)	Recovery Yield (%)	Contamination Rate (%)
Cotton	4400	97.2	96.4	98.3	97.3	88.1	2.1
Polyester	4300	96.7	96.9	97.0	96.9	85.6	2.4
Viscose	3100	95.1	94.7	95.8	95.2	80.9	3.0
Blended Synthetics	4100	94.8	93.9	95.9	94.9	78.7	3.4
Technical Fibers	1800	94.0	92.4	95.1	93.7	76.3	4.6
Overall	19700	95.7	94.9	96.6	95.6	82.8	2.7

Performance Benchmarking

Considering the role of these influencing factors in textile classification and fiber reprocessing, to determine the system's reliability in different industrial environments. This method is used for various test evaluations of the model. Including various fiber materials, different degrees of contamination, textures caused by clothing wear, and a large number of real recycling batches. All experiments used random permutation shuffling to eliminate group differences in the system.

Distribution mapping. Figure 3(a) shows the color value density map of the textile set, with five main user groups. As shown in Figure 3(b), although its scale exhibits relatively stable characteristics, the spatial high-frequency patterns become easier to identify compared to the amplitude differences of the multi-scale texture features. Figure 3(c) shows the spectral characteristics of various fibers in the near-infrared band. Within the

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aforementioned wavelength range, different synthetic materials and cellulose-based fibers respond differently to light. As shown in Figure 3(d), the first three principal components can improve inference speed and scalability while explaining over 86% of the feature variance.

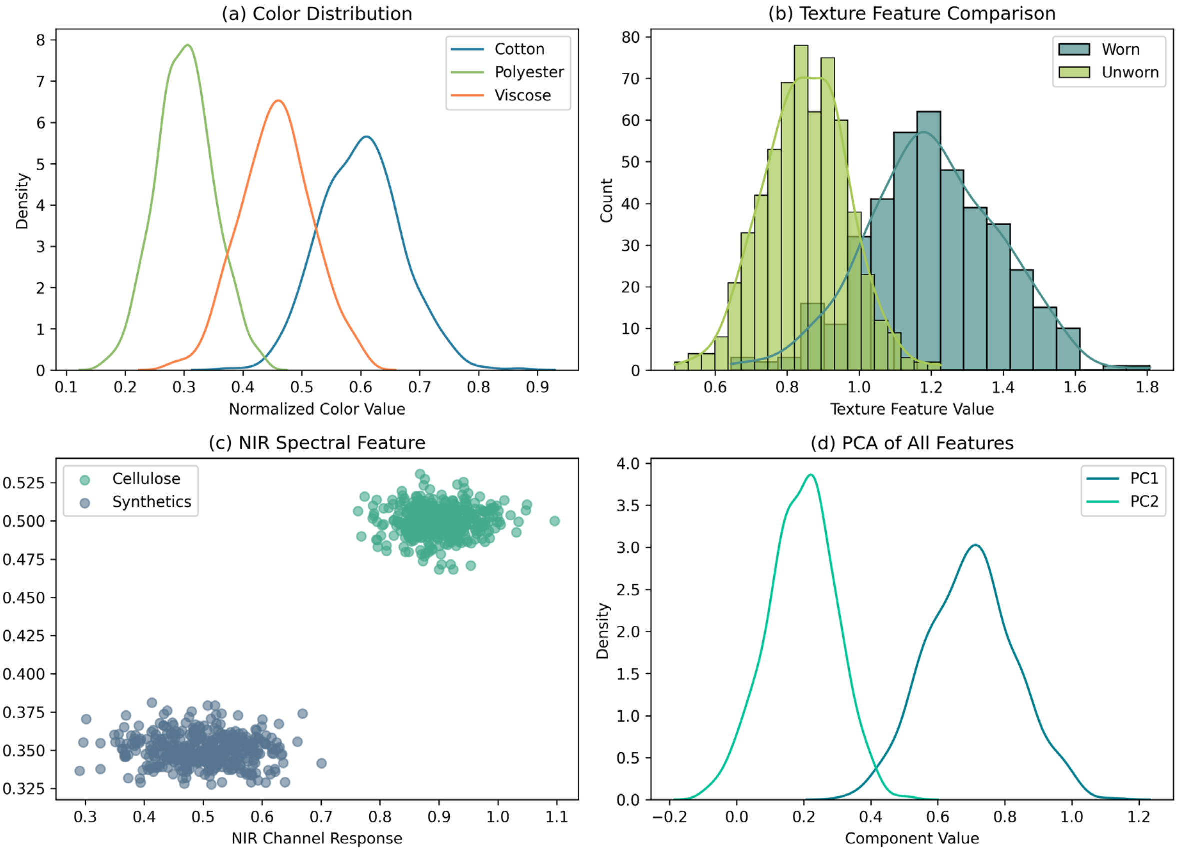

Figure 3. Feature Distribution and Sample Characteristics Analysis:(a) Color Distribution of Textile Samples; (b) Texture Feature Values Comparison; (c) Spectral Attribute Scatter Plot; (d) Principal Component Analysis of Features

Figure 4 shows the performance metrics of all classifiers and different workflow configurations. As shown in Figure 4(a), after deploying the deep convolutional model with multimodal fusion, the overall accuracy reached 97.3%. In terms of industrial model complexity, traditional machine learning methods find it almost impossible to improve performance beyond 93.1%. As shown in Figure 4(b), during the training and validation process, the difference in learning curves indicates that the optimal structure did not overfit, while the final loss of other structures was relatively small. Figure 4(c) shows the variations in F1-Score and recall rate for different fibers. Due to category overlap and image artifacts, specialty technical fibers performed poorly. Cotton and polyester fibers both scored over 96%.

This indicates that the system has significant industrialization potential. Improve the system structure to transmit more data and enhance the accuracy of test model results. In addition to multimodal integration and pipeline design, the goals of data augmentation techniques, including methods like contrastive learning, were also mentioned. These objectives are considered to improve generalization ability in practical applications. Based on contextual comparison and analysis, use statistical or other methods to identify the shortcomings of current vision-guided textile classification and recognition technologies.

Comparative Study with Traditional Methods

Compare the sorting and fiber recovery pipeline of smart textiles with mechanical operations and manual labor. The benchmark platform consists of three components: visual recognition; belt extraction and separation; simple density sorting method. Conduct experimental testing activities in simulated laboratory environments and actual industrial testing platforms. For reference, comparisons should be made at each stage. Due to the

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varying levels of pollution from different locations at different stages for each batch, these differences should also be considered as factors affecting the data results.

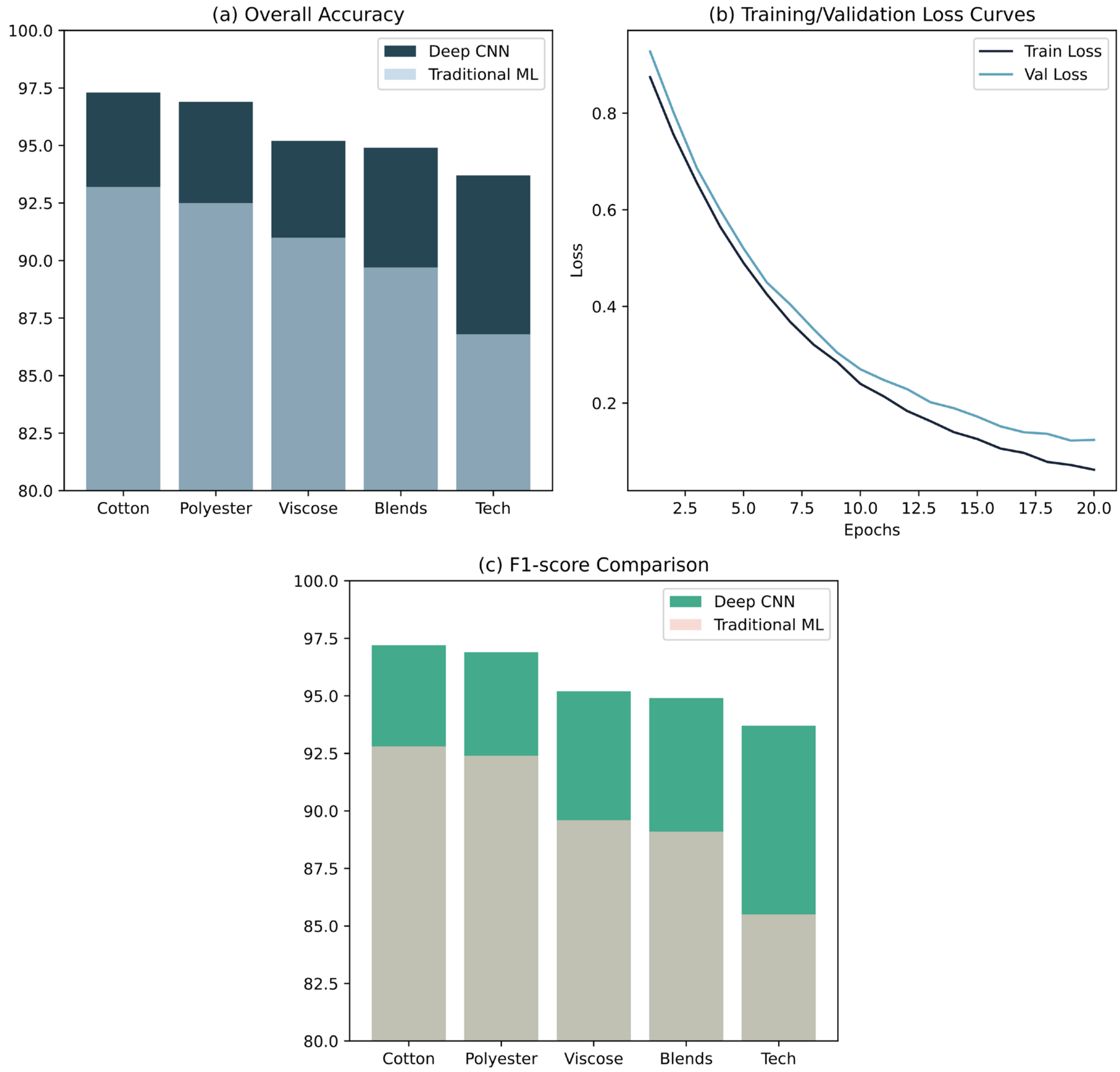

Figure 4. Classification Model Performance Evaluation: (a) Overall Accuracy Comparison among Models; (b) Training/Validation Loss and Accuracy Curves; (c) F1-score and Recall for Different Fiber Types

The confusion matrix used to evaluate the performance of these two methods is shown in Figure 5. As shown in Figure 5(a), the higher-order system exhibits a quite pronounced diagonal dominance, while most off-diagonal deviations occur in a few hard-to-distinguish categories. This indicates that the model has gained more trust and disambiguation capability in distinguishing high-quality technical fibers. Figure 5(b) shows the significant misclassification between types. The appearance of blended fibers and synthetic fibers is very similar, but skilled workers can distinguish between them.

Figure 6(a) shows the relationship between recognition accuracy and target fiber concentration. Only 81% for manual workers, while 96% for the automated system. Figure 6(b) depicts the production. Automation can complete approximately one-third of the manual production volume within the specified time. Figure 6(c) shows the variation in the yield of recyclable fibers. The stability of recycling can be maintained by using high-quality raw materials in subsequent processes.

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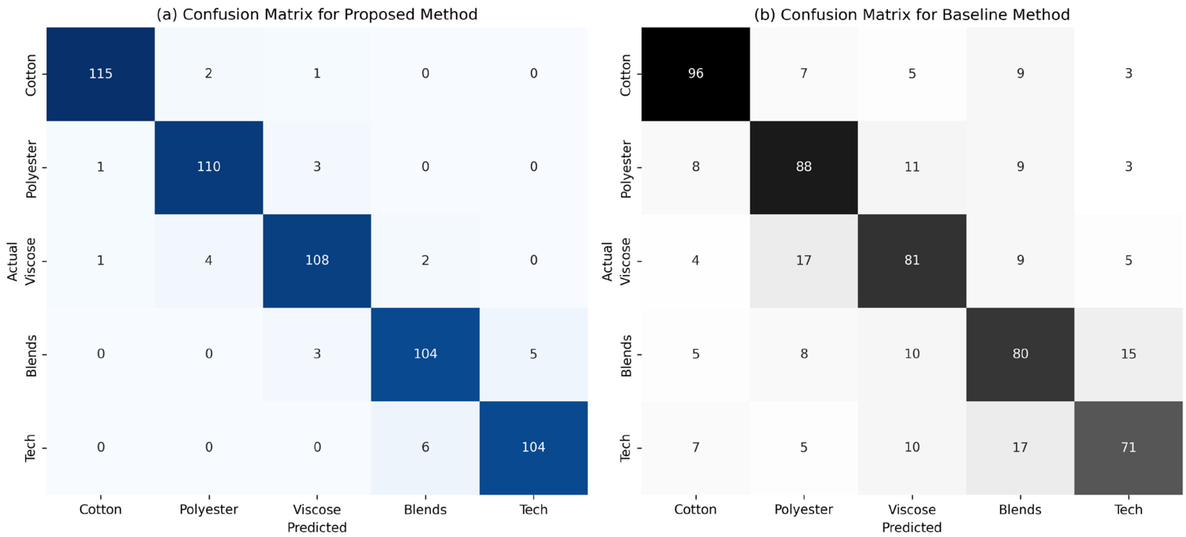

Figure 5. Confusion Matrices of Classification Results: (a) Confusion Matrix for Proposed Method; (b) Confusion Matrix for Baseline Method

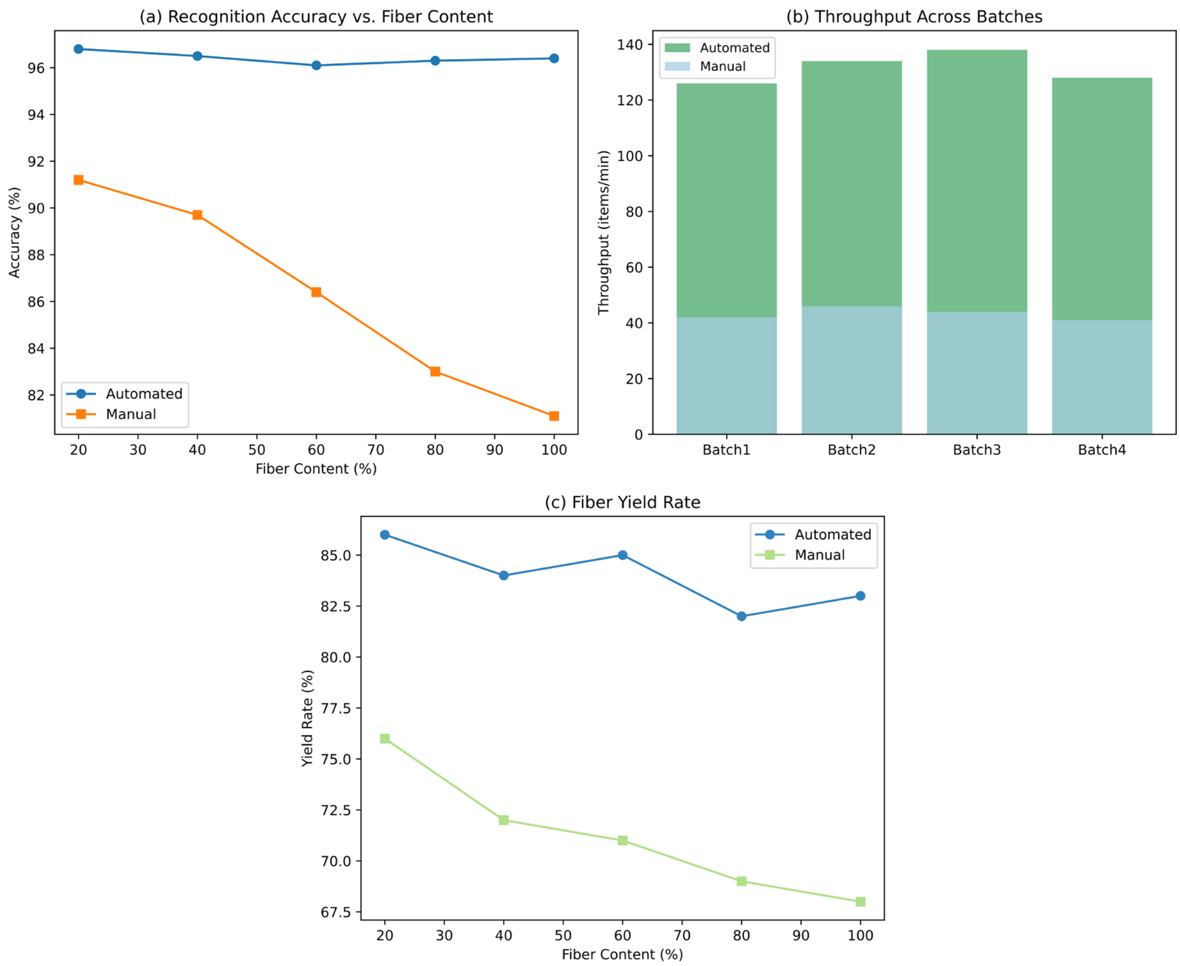

Figure 6. Performance Metrics under Varying Sorting Scenarios: (a) Recognition Accuracy vs. Fiber Content; (b) Sorting Throughput across Different Batches; (c) Recyclable Fiber Yield Rate Trends

Figure 7 shows the changes in key process outcome data. Figure 7(a) shows that the fiber recovery rate increased by more than 9% at all levels of importance. Figure 7(b) shows the reduction in sorting errors, particularly in

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mixed batches. Figure 7(c) shows the increase in unit operating costs due to reduced processing demands and labor.

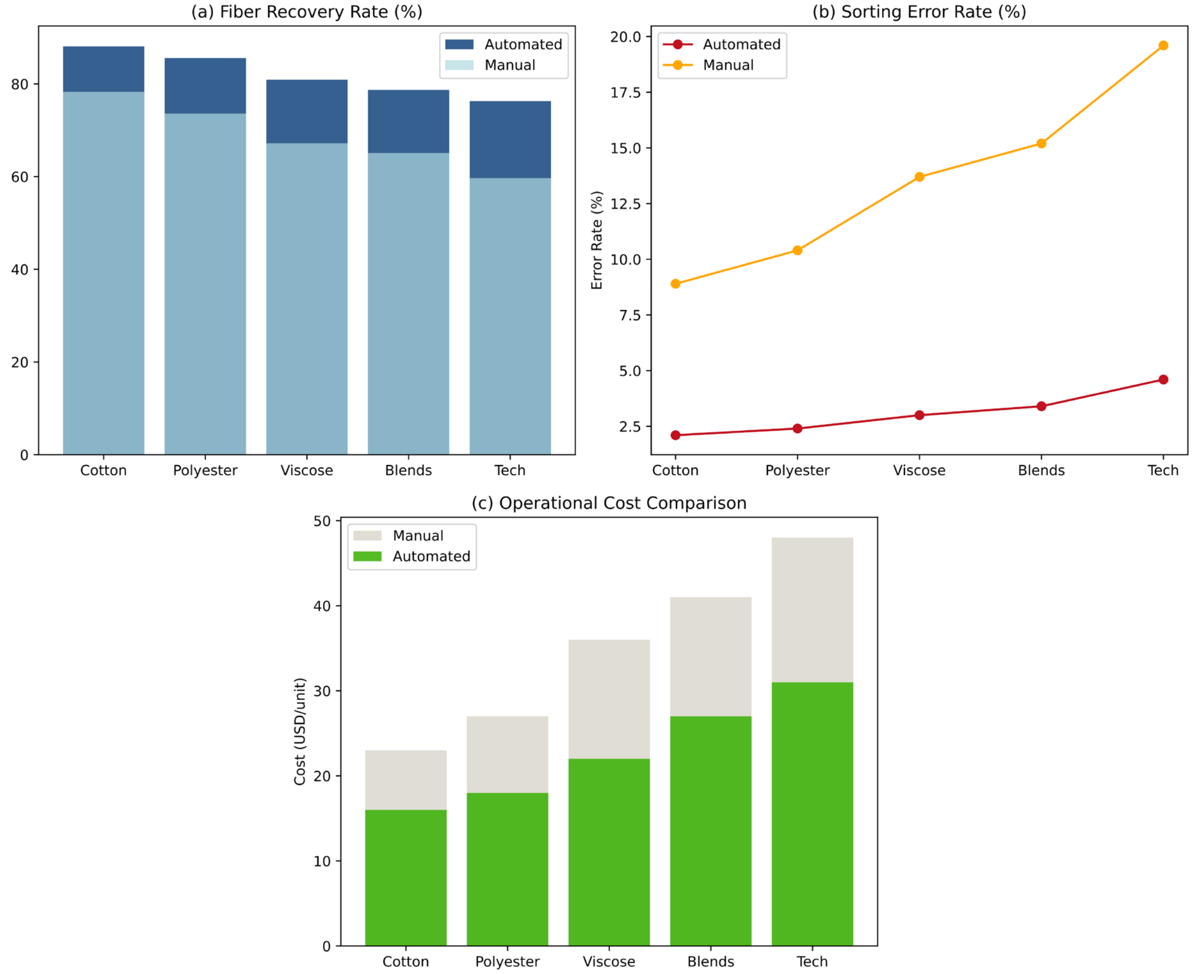

Figure 7. Comparative Analysis of Sorting and Recovery Efficiency: (a) Fiber Recovery Rate Comparison; (b) Sorting Error Rate Reduction; (c) Operational Cost Comparison

Conclusion

Smart textile classification and high-tech fiber recycling are two major advancements in automatic recycling technology. Due to the strong interaction between the sensor-rich hardware structure and the optimized deep learning pipeline, the system in this paper outperforms traditional manual and rule-based mechanical methods in terms of high-precision sorting and high throughput. Comprehensive implementation of the data collection system construction; use effective evaluation tools to revalidate the commercial viability and broad applicability of the research findings.

Achieving relatively accurate fiber identification with low deviation errors in complex real-time environments; this paper suggests using multiple imaging technologies, adaptive process scheduling capabilities, and scale feedback control functions to work stably on various types of waste. According to the reference evaluation, the model's recognition rate exceeds 96%, and the recovery rate exceeds 80%. Using this application can reduce pollution and operational errors. Overall performance has significantly improved, manual entry and reprocessing costs have decreased, and recovery speed has increased by over 17%.

From a technical perspective, this industry is the same. The design of pilot projects may establish a widespread recycling infrastructure globally in the future. By automating the precise classification of different types of textiles, both the quantity and quality of recycled materials are improved, supporting a closed-loop utilization cycle and promoting more environmentally friendly production methods.

By using modular and containerized system designs, it is possible to quickly enter existing or new markets. Using high-quality soft sensor analysis technology to provide real-time quality control data; continuously optimizing algorithms to enhance their ability to withstand severe material fuzziness; the ability to continuously learn from changing fiber mixtures. The platform's multimodal perception, adaptive process control, and data-driven optimization are truly useful concepts. Automated plastic sorting, electronic waste dismantling, and mixed composite material manufacturing technologies are important pathways to achieving the next generation of green industries.

Author Contributions

Bartosz Dabrowski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

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