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Systematic Review

A Systematic Literature Review—AI-Enabled Textile Waste Sorting

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Abstract: The textile and apparel industry faces significant sustainability challenges due to the high volume of waste it generates and the limitations of current recycling systems. Automation in textile waste management has emerged as a promising solution to enhance material recovery through accurate and efficient sorting. This systematic literature review, conducted using the PRISMA-guided PSALSAR methodology, examines recent advancements in computer-based sorting technologies applied in textile recycling. This study identifies and evaluates major technological methods often integrated with machine learning, deep learning, or computer vision models. The strengths and limitations of these approaches are discussed, highlighting their impact on classification accuracy, reliability, and scalability. This review emphasizes the need for further research on blended fiber detection, data availability, and hybrid models to advance automated textile waste management and support a sustainable circular economy.

Keywords: textiles and apparel; sustainability; waste management; artificial intelligence (AI); recycling; sorting; spectroscopy; hyperspectral imaging

1. Introduction

In pursuit of sustainability over recent decades, stakeholders from civil, commercial, and government interests have collectively initiated efforts to mitigate industrial practices that harm humanity and the natural environment. The United Nations (1987) defines sustainability as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" [1]. The literature broadly suggests that three interrelated pillars constitute the sustainability concept: the environment, society, and the economy [2], and they should be considered collectively when making business decisions [3].

The global scope and labor-intensive nature of apparel supply chains provide a risky operating environment for industry incumbents, which increases the likelihood of negative outcomes for nature and society. Researchers note the breadth of environmental impacts arising from raw material production and processing, yarn, fabric and garment production, distribution, consumption, and disposal [4]. Though researchers have begun to incrementally respond to many of these challenges through material and process innovation, barriers to implementing these solutions remain prevalent in the industry (e.g., cost, technology scalability, lack of regulation) [5,6].

Among the challenges facing the industry today, the ability to recycle garments into new or different products continues to elude experts due to an inability to automate fiber recognition in the initial stages of the textile waste management process [7,8]. Yet, the

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need for advances in apparel recycling is eminent, given the market forces that continue to drive fast-fashion consumption, which shortens product life cycles [9,10], increases resource consumption (e.g., fiber, materials, water, energy, and equipment), and generates pollution at all points in the supply chain [11]. In the USA, the frequency and volume of apparel and home textile consumption contribute significantly to landfill waste. According to the Environmental Protection Agency (EPA), the US disposed of 11.3 million tons of textile waste into landfills in 2018, accounting for 7.7 percent of total municipal waste for that year [12]. In addition, the prevalence of synthetic textiles exacerbates environmental impacts through slow decomposition and chemical and microplastic contamination [13–15].

Recent industry reporting approximates that only twenty-three percent of discarded clothing is collected for recycling, of which a scant one percent generates recovered fibers that are suitable for recycling into new materials [16,17] (Figure 1). Accurate fiber sorting is critical for effective apparel classification, which is predominantly performed manually by humans. However, numerous shortcomings arise from manual sorting (e.g., lack of efficiency, human error, and product contamination), which prevent effective textile and apparel recycling [18,19].

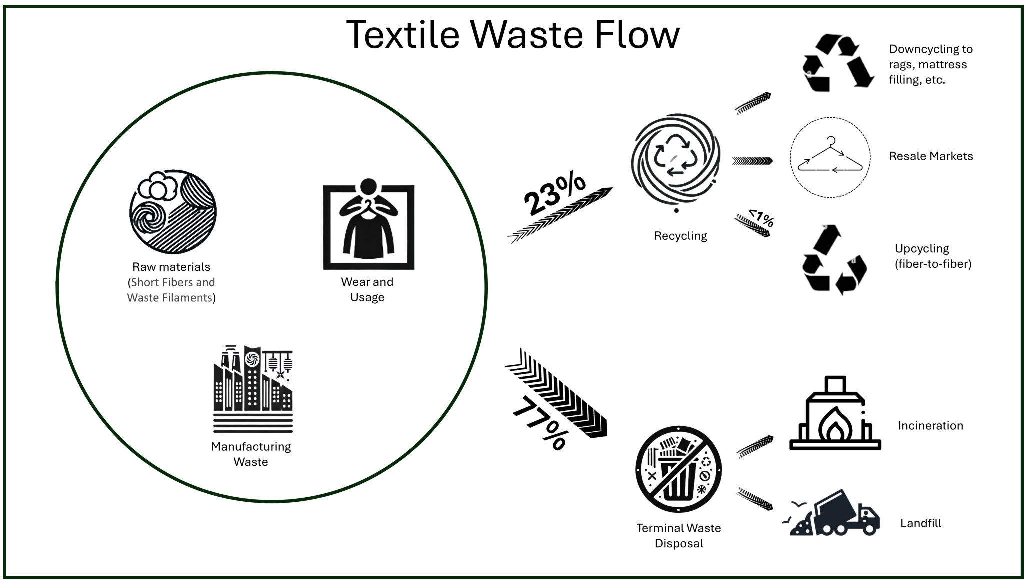

Figure 1. Illustration of textile waste flow from its origin to final disposal.

Stakeholders have begun to develop methods to automate post-consumer textile sorting using Artificial Intelligence (AI) to facilitate circularity [20,21]. In this paper, computer-based sorting technologies refer to automated systems that support textile waste sorting. These include a range of AI-enabled methods, where data-driven algorithms are used to extract features, optimize performance, and improve classification within sorting applications. Primarily, machine learning (ML) algorithms have been developed and tested to classify fibers based on various approaches. However, robust ML algorithms that are capable of effectively classifying blended textile fibers in varying proportions continue to evade academics and developers, suggesting a need to develop novel modeling approaches to address the sorting problem [22].

The purpose of this review is to comprehensively examine the recently published research that considers automation in textile waste sorting to critically evaluate the advantages and limitations of current and developmental technologies. Specifically, the review focuses on the impact(s) of classification algorithms on accuracy and efficiency in textile waste classification. Through contrasting the features of emerging ML approaches to classification, this review provides a foundation for improving model development to address the critical sorting problem from academic and practical perspectives.

The methodology used in this study is outlined in Section 2, resulting in cataloging 17 scientific papers. After data collection, a single study that was published after the original SLR [8] was incorporated into the study. In Section 3, the contents of the 18 cataloged papers are dissected and an in-depth review of the data input methods (spectroscopy-based, imaging, and hyperspectral imaging) and the computer-based data analysis techniques are provided. In conclusion, Section 5 summarizes the outcome.

2. Method

The PSALSAR methodology, structured in accordance with the PRISMA Checklist (Supplementary Materials) [23], was employed to ensure an accurate and replicable execution of the SLR [24]. This framework encompasses the following sequential steps: (i) Protocol, formulation of the study's objective; (ii) Search, identification of relevant publications in four commonly used databases for the textile industry; (iii) Appraisal, determination of criteria for paper selection; (iv) Synthesis, categorization of selected works and establishing the catalog; (v) Analysis, examination of the cataloged studies; and (vi) Report, presentation of the SLR findings. The implementation of steps (i)–(iv) are detailed below, step (v) is discussed in Section 3, step (vi) is addressed in Section 4, and this paper is concluded in Section 5.

2.1. Protocol

Motivated by the growing negative impacts of textile and apparel waste on the environment, this review aims to evaluate emerging research on efforts to automate textile sorting for recycling.

2.2. Search

Four academic databases, Compendex, Web of Science, Textile Technology Index, and Google Scholar (GS), are used to search for pertinent research to provide a comprehensive evaluation of the area in relation to textile recycling and sorting. With the exception of GS, all databases support advanced search features that improve query efficiency and accuracy. The following search criteria were used to direct the literature queries: (a) articles published between 2020 and 2025, (b) keywords present in the title or abstract, (c) papers written in English, (d) papers published in peer-reviewed journals (exclusion of reviews, conference proceedings, practical reports, and non-academic publications).

GS lacks auto-filtering capabilities for requirements (b) through (d), but it does allow filtering for year (requirement (a)). As a consequence, manual filtering became necessary to meet the querying criteria. Two sets of terms covering the general domain related to the central purpose were created to serve as keywords (Table 1). A total of 42 query combinations were generated to search for relevant scholarly articles, with each query including one term from each group in the GS search. For example, one query was structured as "Textile Waste Sorting" AND, convolutional neural network, "CNN", while additional filters such as year range (2020–2025) and language (English) were applied to refine the results. Search strings for the Compendex, Web of Science, and Textile Technology Index databases are presented in Table 1. As a result of initial and filtering activities, the initial article pool consisted of 2197 documents.

Table 1. Search terms and total number of publications by database.

DB [1]	Searching String and Searching Terms	#Articles	Date [2]
Compendex	((((((textile recycling) OR (textile lifecycle) OR (clothing lifecycle) OR (textile waste sorting) OR (automated waste sorting) OR (textiles sustainability)) WN TI) OR (((textile recycling) OR (textile lifecycle) OR (clothing lifecycle) OR (textile waste sorting) OR (automated waste sorting) OR (textiles sustainability)) WN AB)) AND ((((Automated) OR (Automation) OR (Automatic) OR (Machine learning) OR (computer vision) OR (CNN) OR (image processing)) WN TI) OR (((Automated) OR (Automation) OR (Automatic) OR (Machine learning) OR (computer vision) OR (CNN) OR (image processing)) WN AB))) AND (((2025 OR 2024 OR 2023 OR 2022 OR 2021 OR 2020) WN YR) AND (ja WN DT) AND (cpx WN DB) AND (english WN LA)))	167	15 December 2024
Web of Science	(((TI = (clothing lifecycle OR Textile lifecycle OR Textile recycling OR Textiles Sustainability OR Automated Waste Sorting OR Textile Waste Sorting)) OR (AB = (clothing lifecycle OR Textile lifecycle OR Textile recycling OR Textiles Sustainability OR Automated Waste Sorting OR Textile Waste Sorting))) AND (((TI = (Automated OR Automation OR Automatic OR Machine Learning OR CNN OR Computer Vision OR Image processing)) OR (AB = (Automated OR Automation OR Automatic OR Machine Learning OR CNN OR Computer Vision OR Image processing))) AND ((PY = (“2024” OR “2023” OR “2022” OR “2021” OR “2020”)) AND (DT = (“ARTICLE” OR “PROCEEDINGS PAPER”)) AND (LA = (“ENGLISH”)) NOT (DT = (“REVIEW”)))))	183	18 December 2024
Textile technology index	((TI Textile lifecycle OR TI textile recycling OR TI clothing lifecycle OR TI Textiles Sustainability OR TI Automated Waste Sorting OR TI Textile Waste Sorting) OR ((AB Textile lifecycle OR AB textile recycling OR AB clothing lifecycle OR AB Textiles Sustainability OR AB Automated Waste Sorting OR AB Textile Waste Sorting))) AND ((TI Automated OR TI Automation OR TI Automatic OR TI Machine Learning OR TI CNN OR TI Computer Vision OR TI Image processing) OR (AB Automated OR AB Automation OR AB Automatic OR AB Machine Learning OR AB CNN OR AB Computer Vision OR AB Image processing))	8	20 December 2024
Google Scholar	**Group 1**: (“Textile Waste Sorting”, “Textile Lifecycle”, “Textile Recycling”, “Clothing Lifecycle”, “Textiles Sustainability”, “Automated Waste Sorting”) **Group 2**: (“Automated”, “Automation”, “Automatic”, “Machine Learning”, “Computer Vision”, “CNN”, “Image Processing”) ***Each** *subject in Group 1 will be* ***AND****ed with each subject in Group 2. This means a search will be conducted for publications that contain both a subject from Group 1 and a subject from Group 2 within the 2020–2025 period.*	1839	22 December 2024

[1] Database. [2] Date of acquisition.

2.3. Appraisal

Using advanced filtering methods supported by Compendex, Web of Science, and Textile Technology Index databases, inclusion and exclusion criteria were executed during the search (Table 2). However, following the search, manual review of each individual article was undertaken to remove duplicates, studies lacking relevance, and articles that did not meet the quality requirement (not published in journals within the high-quality quartiles Q1 or Q2).

Duplicate Removal: Duplicate articles were eliminated from the original pool to prevent repetition and ensure an accurate analysis. Digital Object Identifiers (DOIs), a distinct alphanumeric string that is assigned to every article for identification, were compared during this process. The paper pool shrank from 2197 to 693 unique publications by removing entries with the same DOIs, to ensure no study was counted more than once.

Table 2. Eligibility criteria established during the appraisal phase.

Eligibility Criteria	**Decision**
Keywords exist in the article's title or the abstract section of the paper	Inclusion
Is published in a peer-reviewed journal	Inclusion
Studies published post-2020	Inclusion
Written in English	Inclusion
Is duplicated within the search documents	Exclusion
Papers published in Q3/Q4 journal quality quartiles	Exclusion
Conference papers, practice materials, reviews, books, or thesis documents	Exclusion
Articles lacking a pair of Group 1 [a] and Group 2 [b] keywords in the title or abstract	Exclusion

[a] Group 1: Textile Waste Sorting, Textile Lifecycle, Textile Recycling, Clothing Lifecycle, Textiles Sustainability, Automated Waste Sorting. [b] Group 2: Automated, Automation, Automatic, Machine Learning, Computer Vision, CNN, Image Processing.

Content-Based Exclusions: To further narrow the pool, only original research publications were selected through a manual review procedure. Identifying specific keywords in the titles and abstracts, papers classified as reviews, conference proceedings, or practical reports were eliminated. To confirm the methodology and focus of the study, the abstracts were also reviewed. A total of 405 papers remained in the pool following this filtering procedure. As mentioned above, manually reviewing each article was necessary, particularly due to the lack of query features in the GS database. In this step, all possible combinations of phrases from the two groups defined in Table 2 were searched in the full text of each article. This served as an effective method for filtering out unrelated papers from the pool.

Quality Assessment: Journal quartiles were used to filter articles based on quality. Scholarly rigor, impact, and citation rates are often higher for journals listed in Q1 and Q2. In an effort to preserve the validity and integrity of the review, articles published in journals that were ranked outside of Q1/Q2 were eliminated. These quartile rankings were determined using the Scimago website [25], an online resource that rates journals according to scientific metrics, including citations and research productivity. Furthermore, articles from journals lacking quality ratings were not included. After removing articles that did not meet the quality criterion, 309 articles remained in the pool.

2.4. Synthesis

A multistep manual review procedure was used to ensure that only relevant articles remained in the pool. Initially, the title and abstract of each article were skimmed to determine its relevance to automation in textile sorting and recycling. The goal of text skimming was to identify automation-related techniques in the articles. Papers that were determined to be completely unrelated have been eliminated. A total of 44 articles passed this skimming stage and a full text screening was performed to determine their final inclusion in the research. This process was a critical phase in our systematic literature review, during which 17 articles were identified for a comprehensive and detailed study. These articles were subjected to a thorough examination, with particular attention given to their methodologies to ensure alignment with the objective of the review. Each article successfully met all predefined criteria outlined in Table 3, confirming their relevance and quality for inclusion in our analysis. Following this in-depth review, a comprehensive summary comparison of the findings of these articles was meticulously prepared and is presented in the Results section. This stage allowed us to extract valuable information and evaluate the methodologies employed in the selected studies, contributing to a robust and well-informed review.

Table 3. SLR inclusion criteria for automated textile-sorting methods in the appraisal phase.

Automated Sorting Method	Description	SLR Inclusion Criteria
Spectroscopy	Uses spectroscopy techniques to capture spectral data for identifying textile materials in automated sorting.	Studies must apply spectroscopy techniques with computer-based automation (e.g., ML [1], DL [2], CV [3]) in the textile waste management domain, focusing on the sorting process.
Imaging	Uses traditional imaging methods, such as RGB cameras, to classify textiles based on color and texture differences. However, this approach lacks detailed spectral information for precise material identification.	Studies should employ traditional imaging (e.g., RGB-based) with computer-based automation to assist textile sorting in recycling.
HSI [4]	HSI captures both spatial and spectral data, analyzing each pixel across multiple narrow spectral bands. This enables precise material differentiation beyond what traditional imaging can achieve.	Studies should employ HSI with computer-based automation for textile waste sorting, allowing material classification based on spectral signatures.
Thermal	Employs thermal methods to detect material differences for automated textile classification.	Studies must utilize thermal-based approaches integrated with computer-based automation for textile waste sorting in the recycling stage.

[1] Machine Learning. [2] Deep Learning. [3] Computer Vision. [4] Hyperspectral Imaging.

Figure 2 provides a visual representation of the systematic filtering process applied in this review, following the PRISMA methodology. This diagram illustrates the sequential decision-making process and facilitates understanding of the inclusion and exclusion criteria at each stage. Four distinct categories—spectroscopy, imaging, hyperspectral imaging (HSI), and thermal—emerged from the synthesis that represent technological approaches to perform the automated sorting process in the textile-recycling procedure (as presented in Table 4, the screening process narrowed the selection to 44 articles, with only 17 meeting the inclusion criteria for this systematic literature review). This paper focuses primarily on textile waste sorting, specifically in the recycling stage that employs computer-based automation approaches. Studies using different methods, those from unrelated domains that do not focus on textile products, or those addressing the entire product life cycle rather than recycling-specific sorting were excluded and placed in the "Not Related to Textile Sorting" category, which accounts for 15 articles that were ultimately excluded. Out of 14 papers related to spectroscopy, only 11 met the inclusion criteria. Likewise, nine papers focused on imaging, with only three qualifying for inclusion. In the HSI domain, all three reviewed papers met the criteria. Meanwhile, in the thermal category, none of the three papers screened met the inclusion requirements.

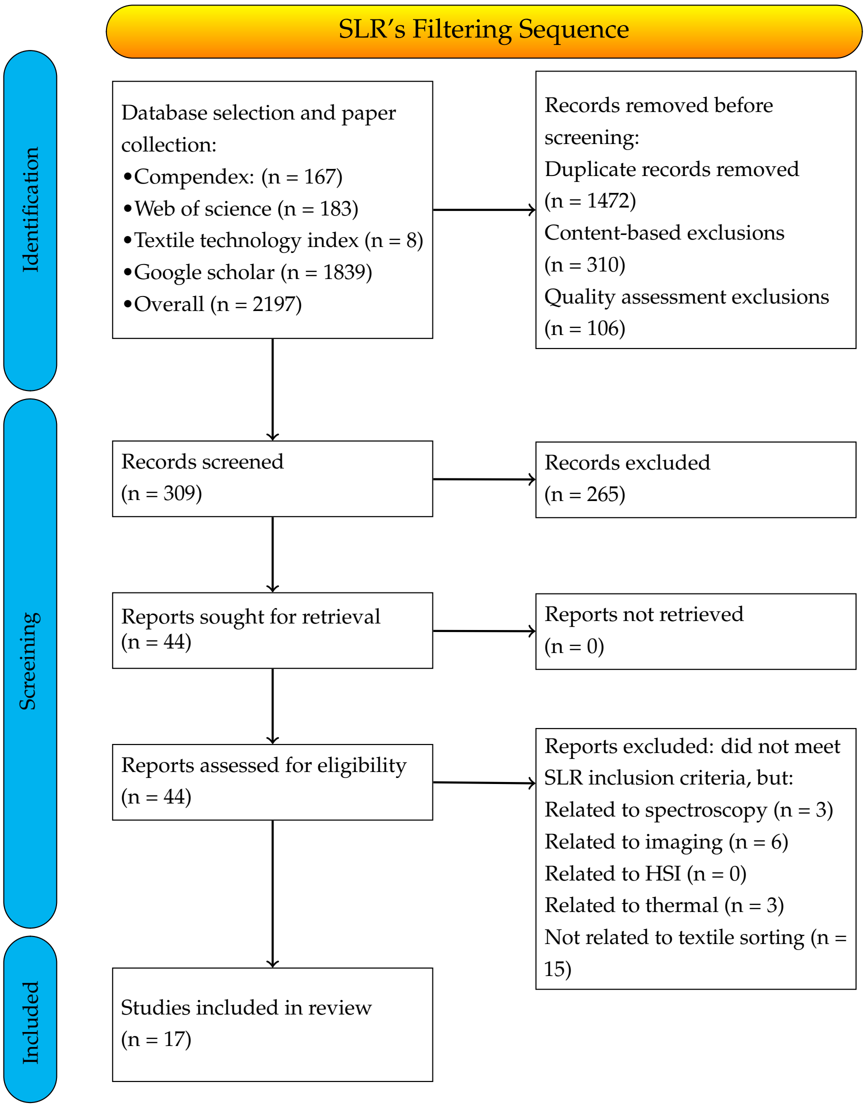

Figure 2. PRISMA 2020 flow diagram shows the sequential filtering procedure where n represents the number of papers captured at each stage.

In the articles excluded from spectroscopy, the main focus was on quality assurance in textile manufacturing, general classification of industrial organic waste, and chemical recycling through solvent-free depolymerization rather than automated textile waste sorting [26–28]. Although these studies used spectroscopy, they did not align with the SLR's focus on spectroscopy-based computer-automated textile waste sorting and are therefore excluded. The main focus of the excluded articles from the imaging category was the defect detection in textile production and the general segregation of landfill waste [29–34]. These topics fall outside of this SLR's scope. Additionally, during the synthesis phase, 15 articles were categorized as "Not Related to Textile Sorting" because they focus on areas outside of automated textile waste sorting. Some explore fiber valorization and general material recycling rather than sorting technologies, while others emphasize energy efficiency, supply chain management, IoT-driven manufacturing improvements, or tag-based approaches for product life cycle monitoring. All of these domains are screened, but are outside of this paper's scope [10,35–48]. Three articles were excluded from the SLR despite their focus on thermal methods because they do not align with the core theme of textile waste sorting and recycling using computer-based approaches. Although they explore thermal properties and applications, such as reducing thermal signatures or fabricating new fibers, they do not involve automated sorting techniques [49–51]. Thermal methods can be beneficial when used in combination with computer-based techniques to improve the accuracy of classification in the textile-sorting process [52]. However, it should be noted that thermal approaches alone can sometimes lead to incorrect results, as the heat involved can alter the surface texture or structure of coated or synthetic fabrics, potentially degrading the reliability of classification [53,54].

Table 4. Summary of the synthesis stage results.

Domain	Screened	SLR Included
Spectroscopy	14	11
Imaging	9	3
HSI	3	3
Thermal	3	0
Not Related to Textile Sorting [1]	15	0
Total	44	17

[1] None of the articles in this set are related to textile, the sorting process, or any aspects of this SLR inclusion criteria.

3. Results

This review process resulted in 17 selected articles that employed computer-based techniques across three primary approaches: spectroscopy, imaging, and HSI technologies. Post-data collection, a single study that was published after the original SLR was incorporated into the study, increasing the total catalog to 18 [8]. The additional study's relevance to the focus justified inclusion for the analysis particularly, given that the study was published three days beyond the query scope.

3.1. Data Input Method

3.1.1. Spectroscopy-Based Methods

Spectroscopy is an analytical technique widely utilized in textile waste sorting, enabling the identification and classification of materials based on their spectral signatures. This method takes advantage of the interaction of electromagnetic radiation with textile fibers to determine their chemical composition, facilitating automated and accurate material differentiation [55]. Various spectroscopy-based approaches have been explored in the literature, including Near-Infrared (NIR) spectroscopy, Attenuated Total Reflectance-Fourier Transform Infrared (ATR-FTIR) spectroscopy, and Short-Wave Infrared (SWIR) spectroscopy, each offering unique advantages in material identification. These techniques are frequently integrated with machine learning and deep learning (DL) models to enhance classification accuracy and efficiency, supporting the transition from manual to automated textile sorting in recycling processes. The following paragraphs provide a detailed examination of the eleven studies included in the spectroscopy category.

Liu et al. (2020) presented a deep learning-based method for qualitative classification of textile waste using NIR spectroscopy [56]. Addressing the inefficiency of manual sorting, they developed the Textile Recycling Net (Tr-Net), a CNN that transforms NIR spectral data into pixelated images for deep learning-based classification. The results indicated that Tr-Net achieved 96.20 percent classification accuracy, outperforming traditional ML approaches, including the SVM and multi-layer perceptron, which suggest accuracies of 83 and 93 percent, respectively. The dataset included 263 textile samples that covered nine material categories, such as pure polyester, wool, cotton, polyester/cotton blends, and nylon. While the study demonstrated a fast, efficient, and non-destructive way (it does not alter or damage the samples) to classify textile waste, the authors acknowledged the need for a larger spectral library to improve robustness and the potential for refining the CNN structure for higher accuracy.

In the same year, Riba et al. (2020) proposed an automated textile classification system using ATR-FTIR spectroscopy to improve textile recycling within a circular economy framework [57]. Their study aimed to replace manual sorting with an automated approach achieving 100 percent classification accuracy for pure natural, artificial, and synthetic fibers. By combining ATR-FTIR spectroscopy with PCA for feature reduction, CVA for dimensionality reduction, and kNN for classification, the study efficiently classified textiles without prior preprocessing treatments. However, a key limitation was the exclusion of blended fabrics, making it unclear how the system would handle mixed fibers, which are common in textile waste. The study concluded that ATR-FTIR with multivariate analysis offers a fast, accurate, and non-destructive sorting solution for large-scale recycling. However, challenges remain in integrating the system for industrial use.

The following year, Cura et al. (2021) investigated the use of NIR for automated textile recognition and sorting, focusing on factors that affect classification accuracy, such as coating, fabric thickness, finishing treatments, and aging [58]. Their results showed that NIR-based sorting could correctly classify textiles in 73 percent of cases, with higher accuracy for monomaterial fabrics such as pure cotton, polyester, and viscose. However, model challenges arise when dealing with blended fabrics, thin textiles, and aged materials, sometimes resulting in misclassification. The study highlighted the importance of a balance between purity and yield in sorting operations, suggesting that as recycling technologies evolve, sorting systems must adapt to blended materials and chemical changes in used or aged textiles.

In 2021, Li et al. developed a qualitative identification model for textile waste using NIR and a BP-ANN to improve accuracy and efficiency in textile sorting [59]. Using a dataset of 892 textile samples, the authors developed a BP-ANN model capable of distinguishing between 11 textile categories, achieving an accuracy of over 99 percent in both internal and external validation (internal validation refers to testing on a subset of the training data, while external validation involves using a completely separate dataset to assess model performance). The study also investigated the effects of fabric thickness and environmental humidity on the collection of NIR data, finding that controlled humidity levels (30–40%) improved spectral stability. Despite the model's effectiveness in general textile waste identification, distinguishing textiles with very low content of one fiber (<5%) in blends remains a challenge. Additionally, the model's classification performance for core yarns, decorative threads, and coated fabrics was uncertain because these textile types were not included in the training or validation datasets, and their complex structures or surface treatments may interfere with accurate NIR spectral analysis.

In 2022, Riba et al. present an automated classification system for post-consumer textile waste using NIR spectroscopy with CNN to enhance textile-recycling efficiency [60]. The study focuses on classifying three textile categories: pure fibers (cotton, linen, wool, silk, polyester, polyamide, and viscose), viscose–polyester blends, and cotton–polyester blends. The two classification approaches are compared: one directly utilizing CNN and the other incorporating PCA (reduces data dimensionality by retaining key variance features) and CVA (enhances class separation for better classification) before classification. The results demonstrate that the PCA + CVA + CNN approach significantly improves the classification accuracy, achieving 100 percent accuracy for pure fibers and viscose–polyester blends while achieving 91.1 percent accuracy for cotton–polyester blends. These findings suggest potential scalability for automated textile sorting, offering a rapid, reliable, and non-contact solution to enhance recycling efficiency. However, the effectiveness of method relies on the availability of a high-quality dataset with accurately labeled textile compositions. A comparison with Riba's 2020 study [57] highlights a key shift from ATR-FTIR to NIR spectroscopy and kNN to CNN model after feature selection. Although the earlier method achieved 100 percent accuracy for pure fibers, it required sensor contact, limiting scalability (where techniques such as ATR-FTIR require physical contact with samples, which can slow down processing and limit automation in industrial settings). The 2022 study improved automation by enabling real-time, high-speed sorting, making the NIR method more scalable for industrial applications. However, challenges remain in classifying blended materials, partly due to the limited number of available samples.

Qi et al. (2022) developed a rapid and non-destructive method to determine the moisture content of various types of solid waste, including textiles, using ATR-FTIR combined with ML models [61]. Their study aimed to improve efficiency over traditional moisture measurement techniques, which are time-consuming and destructive. They tested 20 different combinations of preprocessing and ML regression techniques. For example, a preprocessing technique (Attenuated Total Reflectance (ATR) correction, first derivative, Savitzky–Golay filter, or a combination of first derivative and Savitzky–Golay filter) is combined with an ML regression algorithm (Support Vector Regression (SVR), Partial Least Squares Regression (PLSR), Random Forest (RF), or a hybrid method called SPA-SVR). Among these, the SVR model combined with first-derivative preprocessing, and the SPA-SVR model combined with ATR correction, yielded the best performance. They achieved high precision (R^2 values of 0.9604 and 0.9660 where R^2 is coefficient of determination) with a root mean square error of 3.80. However, the exact number of textile samples that they used in their model was not clearly specified, making it difficult to assess the robustness of their model specifically for textile waste. The study concluded that ATR-FTIR combined with ML provides a promising alternative for real-time monitoring of solid waste moisture content, though limitations included the small detection area of ATR-FTIR and spectral interference from contaminants.

In the same year, Du et al. (2022) introduced an automated recognition and sorting system for textile waste using an online NIR spectroscopy device integrated with CNNs [22]. The AI-driven system classified 13 different textile types, and external tests showed the "CNN1" model achieved a 97.1 percent identification accuracy, while "CNN2" reached 95.4 percent, processing each sample in under two seconds. The system transformed NIR spectral data (901–2500 nm) into grayscale images for CNN processing, significantly improving textile-sorting efficiency. While the study demonstrated high accuracy, challenges included misclassification in certain fiber blends (e.g., polyester/cotton vs. polyester/viscose) and difficulties handling coated textiles remained. Additionally, the reliance on NIR spectroscopy could be affected by fabric thickness and reflectance properties, necessitating further refinements.

Qiu et al. (2023) further investigated the role of moisture in NIR spectroscopy-based textile waste sorting and introduced the External Parameter Orthogonalization (EPO) algorithm to mitigate moisture-related spectral distortions [62]. Moisture was known to cause spectral shifts, particularly around 1150 and 1450 nm, decreasing the classification accuracy. By applying EPO, the study significantly improved the performance of various ML and DL models, including Partial Least Squares (PLS), Decision Trees, Random Forest, Gradient Boosting Decision Trees, SVM, and convolutional neural networks (1D-CNN, 1D-Inception-CNN). The dataset consisted of 216 textile samples of polyester/viscose waste scanned under varying moisture conditions. The authors reported that the average R^2 score (coefficient of determination) across eight ML models was only -1.955 before EPO, which significantly improved to 0.83 after applying the algorithm, with Random Forest achieving the highest R^2 of 0.90. While the study demonstrated a rigorous methodological approach, its primary limitation was its exclusive focus on polyester/viscose blends, which left questions about the generalizability of EPO to other textile compositions.

In 2023, Iezzi et al. introduced a novel method for textile sorting and tracing by embedding photonic crystal fibers (PhC fibers) into textiles, providing a permanent, automated identification solution [63]. The study addressed the limitations of conventional textile-labeling methods, such as care labels, radio frequency identification (RFID) tags, and QR codes, which are often inaccurate, removable, or cost-prohibitive for large-scale adoption. The researchers developed and characterized polymer-based photonic fibers with over 100 alternating layers of polycarbonate and polymethyl methacrylate (PMMA), using thermal drawing techniques to create tunable optical signatures. These fibers exhibit unique reflectance patterns in the NIR and mid-infrared spectra, making them readable via industrial spectroscopy-based sorting systems. The fibers maintain strong reflectance peaks that improve sorting accuracy, overcoming issues with overlapping absorption peaks in fiber blends that have hindered traditional NIR-based classification. To model and predict optical responses, the authors used the STACK solver within the Lumerical FDTD simulation suite, allowing for precise simulation of multi-layer reflectance behaviors based on wavelength-dependent refractive indices. The study demonstrates that these fibers can be mass-produced at low cost, woven seamlessly into textiles without altering their appearance, and successfully read using standard infrared spectroscopic methods. However, a notable limitation is that the study only tested the photonic fibers in polyethylene (PE) and nylon fabrics, without evaluating their performance in cotton, wool, polyester, or other common textile materials, which are crucial in real-world textile waste streams. Additionally, the long-term durability of these fibers under industrial washing, mechanical stress, and wear conditions has not been extensively evaluated, which is critical for real-world deployment. The authors conclude that this technology could significantly enhance textile recycling and counterfeit detection by enabling highly efficient automated sorting at all life cycle stages. However, the practical deployment of this technology in real-world sorting facilities still requires further validation, particularly regarding large-scale fiber integration and long-term durability under industrial laundering and wear conditions.

In 2024, Johns et al. presented a novel approach to identify common textile microplastics using autofluorescence spectroscopy combined with k-means cluster analysis [64]. The study focuses on the need for rapid and accurate identification of polymer-based microplastics in environmental and industrial applications because different techniques (FTIR and Raman spectroscopy) can be time-consuming and labor-intensive. The authors investigated how the autofluorescence properties of polymers can serve as unique spectral fingerprints for microplastic classification, particularly considering the impact of aging and dyeing on spectral variations. Using k-means clustering, the study successfully differentiated seven common textile materials (acrylic, polyester, nylon, polyethylene, polypropylene, cellulose (cotton), and wool) achieving an accuracy of 71 percent with only a few spectral inputs. This method presents a promising avenue for real-time, automated microplastic identification at a much faster rate than traditional spectroscopic techniques. However, while the approach significantly improves speed, accuracy remains moderate, suggesting that further refinements, such as hybrid models that incorporate additional spectral features or ML advancements, may be necessary. The study highlights the potential of autofluorescence spectroscopy in textile waste management. However, leaving the study of polymer blends behind can be a potential limitation.

Published in 2024, Bonifazi et al. proposed a classification approach for end-of-life textiles using SWIR spectroscopy to enhance textile sorting for recycling [65]. The study introduced a hierarchical classification procedure that utilizes PLS-Discriminant Analysis (PLS-DA) to distinguish textiles based on the origin of the fiber and further classify them into specific material types. Their approach demonstrated strong potential for automation, achieving an overall accuracy of 98.4 percent. However, the classification performance varied across materials, with perfect accuracy for wool and silk but lower sensitivity for certain blends (e.g., viscose–polyester blend at 40 percent). Although SWIR spectroscopy offers a scalable solution, it only analyzes surface-level material composition, potentially limiting its effectiveness in textiles with coatings or multi-layered structures.

Tsai and Yuan (2025) present an advanced automatic textile-sorting system that combines Raman spectroscopy with a suite of AI techniques, including ML and DL models, to classify textile waste based on fiber composition [8]. Their work addresses the challenge of mixed-fiber textiles in recycling by sorting materials into six distinct fiber-based classes, such as pure polyester, pure cotton, and polyester–cotton blends. The system integrates high-resolution spectral data collected from 225 textile samples with AI models including kNN, SVM, Random Forest, ANN, and CNN. Raman spectra were preprocessed and, for ML models, reduced using PCA (from 342 to 15 dimensions) to improve classification efficiency. Among all models, the Artificial Neural Network (ANN) achieved the highest performance, reaching 96.9 percent testing accuracy, and outperformed CNN and all other ML models in test classification. The SVM model, although highly accurate with 99 percent validation accuracy, showed high variance (4.9%), indicating instability across data splits. A major strength of this study is its integration of spectroscopy with AI to support closed-loop recycling by improving material purity, a key need in the circular economy. However, limitations are also notable: the dataset is relatively small and was collected under controlled laboratory conditions, and textiles with heavy dye interference (e.g., dope-dyed garments) were removed from the analysis due to fluorescence distortion, which limits generalizability. In addition, imbalanced classes required artificial upsampling, and rare fiber types were underrepresented. Also, the exact method and extent of upsampling were not described. While the study shows strong promise and innovation in textile-sorting automation, the reported accuracy should be interpreted cautiously, as further validation on larger and more diverse real-world samples is essential.

3.1.2. Imaging Methods

Imaging methods relying on RGB images play a significant role in product classification, particularly in distinguishing objects based on shape, color, texture, or surface patterns [29–32]. These methods use conventional cameras to capture visual information, where each pixel contains three color values (red, green, and blue) representing the visible spectrum. Unlike spectroscopy, RGB-based classification methods do not analyze detailed spectral signatures but instead rely on visual features extracted through image processing and ML techniques [66–68]. In textile recycling, imaging-based approaches can help differentiate materials based on patterns and color distributions [32,69]. These methods often integrate DL models such as CNN to improve accuracy for complex classification tasks. However, the main limitation of RGB-based classification is its inability to distinguish materials with similar visual characteristics but different chemical compositions, which makes it less effective for material identification compared to hyperspectral or spectroscopy-based methods. Nonetheless, its affordability and ease of implementation have contributed to its widespread use in industrial automation.

Sun-Kuk Noh conducted research focusing on classifying recycled clothing based on garment type rather than fabric composition, meaning it distinguished between clothing items like jeans, shirts, and jackets but did not differentiate between materials such as cotton, polyester, or wool [70]. The research proposed a recycled clothing classification system that integrated the Internet of Things (IoT) and DL, specifically leveraging AlexNet for clothing classification. The system used a Raspberry Pi camera to capture images of garments on a conveyor belt, which were then processed through a pre-trained AlexNet model to classify clothing into nine categories (e.g., jeans, shirts, jackets). The study used a dataset of 3300 images, consisting of 2400 “clean” images (garments without crumpling or folding) and 900 “loss” images (garments that were crumpled or folded), to train and test the model. The reported overall classification accuracy was 68.28 percent, with clean images achieving 74.2 percent accuracy and crumpled images achieving 53.33 percent accuracy. While these results demonstrated the feasibility of AI-based automation in textile recycling, they also highlighted challenges related to image quality and garment deformation. The transfer learning approach allowed features from pre-trained CNN features to be adapted for clothing classification, but the dataset remained relatively small for DL applications. The main contribution of the study was to show that AI could replace manual labor in sorting and categorizing used textiles, potentially improving efficiency and standardizing the recycling process. However, the accuracy was still below optimal levels, suggesting that additional dataset expansion and model refinement may be required to ensure reliable real-world implementation.

In 2023, Furferi and Servi explored the automation of color classification in recycled wool fabrics through a machine vision-based system integrated with a probabilistic neural network [71]. Given that color classification in textile recycling is often performed manually by expert operators, the authors aimed to develop a more efficient and automated solution. Their system successfully classified plain-colored regenerated wool fabrics with an overall reliability index of 83.2 percent, which was competitive compared to other machine learning-based approaches in textile classification. The methodology involved image acquisition using a machine vision system, which captured high-resolution images of fabric samples under controlled lighting conditions. The images were then processed using an indexing algorithm that mapped them onto a predefined RAL (Reich Committee for Delivery Conditions, a standard color-matching system) color chart, limiting the color classification complexity while preserving critical color information. The dataset comprised 800 samples, categorized into 10 color families and 40 specific color classes, with additional validation on 200 new fabrics. The training process involved normalizing the extracted color data and feeding it into a PNN, which assigned probability scores to different color classes based on input features. The final classification was determined by the highest probability match. The main conclusion of the study was that the proposed system provided a reliable, cost-effective approach for color sorting in textile recycling, offering a significant step towards automation in an industry that still heavily relies on manual sorting. However, while the method demonstrated strong classification accuracy for most color families, it performed less effectively in differentiating black and gray shades. Additionally, its reliance on a predefined set of color classes can limit its adaptability to more complex, multicolored, or patterned textiles. Despite these limitations, the study presented a valuable contribution to textile waste management by enabling more standardized and scalable color classification.

In 2024, Tian et al. present a machine vision-based system integrating attention mechanisms for the qualitative classification of waste garments [72]. The study highlights the challenges of automated classification due to visual complexities like deformations, occlusions, and similar colors, which hinder accurate identification. To overcome these issues, the authors propose an adaptive permutation attention module integrated in CNN to enhance feature extraction. Using a dataset of 27,000 annotated garment images collected via an industrial conveyor-based sorting system, the model was trained and benchmarked against existing approaches. The proposed model significantly outperformed traditional CNNs, improving classification accuracy from 68.28 to over 90 percent, reaching human-level performance. A two-week real-world deployment demonstrated the system’s stability and robustness in dealing with visual complexities. The study concludes that attention-enhanced DL models can provide more reliable automated garment classification, reducing labor costs, and improving recycling efficiency. However, the method remains limited to visual classification and does not address fiber composition differentiation, which remains a challenge for textile waste-sorting technologies.

3.1.3. Hyperspectral Imaging Method

HSI represents a transformative approach in material analysis by integrating the strengths of both traditional spectroscopy and traditional imaging, making it a hybrid method that offers both spatial and spectral information [73]. Unlike traditional spectroscopy, which captures spectral data for a single point or small area, HSI extends this capability by recording hundreds of narrow, contiguous spectral bands for every pixel in an image. In contrast, traditional imaging methods, such as RGB-based imaging, only capture three broad spectral bands (red, green, and blue), which means that each pixel contains only three values. However, HSI provides significantly more spectral values per pixel, covering a wide range of wavelengths beyond visible light [73]. This allows for much more detailed material differentiation, as each pixel carries a full spectral signature instead of only three color values. Therefore, HSI forms a three-dimensional hyperspectral data cube. This capability enables precise material identification by analyzing how different materials absorb and reflect light across multiple wavelengths. Advancements in HSI have expanded its applications in all industries, including precision agriculture, medical diagnostics, food quality assessment, etc. [74,75]. One of the most significant industrial applications of HSI is in textile waste management and recycling. HSI makes it possible to accurately classify textile fibers like cotton, polyester, wool, and rayon, even when they appear visually similar. The following paragraphs provide a review of the studies selected for this SLR.

In 2020, Mäkelä et al. presented a machine vision approach for estimating polyester content in recyclable textile waste using NIR, addressing the need for rapid, non-destructive, and automated textile sorting [76]. The study's main outcome was the development of an image regression model capable of predicting polyester content with an average error of 2.2–4.5 across a range of 0–100 percent polyester samples. This method enhanced the ability to classify and sort textiles, which is critical for large-scale recycling operations where chemical or mechanical separation depends on accurate material characterization. The study employed hyperspectral imaging combined with PCA and PLS regression (PLS-R), leveraging spatial and spectral data to estimate the polyester content of blended textiles, including polyester/cotton, polyester/viscose, polyester/lyocell, and polyester/recycled cotton. The dataset consisted of 33 textile samples, covering both pure and blended materials, though the exact number of blended samples was not explicitly stated, which limited the ability to assess the model's performance across different blend ratios. The methodology refined the model by reducing prediction errors while improving calibration. The authors concluded that their approach provided a viable alternative to destructive chemical analysis, facilitating large-scale automation in textile sorting. A key advantage of this study was its non-destructive nature and high accuracy compared to traditional methods. However, challenges remained, particularly in handling variations caused by surface properties and multi-layered textiles, which introduced inconsistencies in spectral readings. While the method showed promise for industrial applications, its accuracy could be further enhanced with a larger dataset and real-world testing in automated sorting facilities.

Later in 2022, Huang et al. presented a novel approach for the non-destructive classification of textile fibers using HSI and a one-dimensional convolutional neural network (1D-CNN) [77]. The study highlighted the limitations of traditional fiber identification methods, which are often labor-intensive, time-consuming, and even destructive. The proposed method leveraged HSI, which captures spectral information across multiple wavelengths, and applied DL to automate and enhance textile fiber classification. The results demonstrated that the 1D-CNN model outperformed traditional ML approaches such as kNN, SVM, Random Forest, and PLS-DA. Specifically, the 1D-CNN model achieved an impressive accuracy of 98.6 percent, compared to Random Forest's 91.4, while significantly improving classification speed and efficiency. The model was particularly successful in distinguishing complex fiber compositions, making it a promising tool for automated textile sorting and recycling. While the dataset included 600,404 spectral data points (this is the number of pixels) from different fiber types, the limited number of unique fiber types may reduce the model's generalizability in real-world applications, where fiber blends and treated fabrics are more common. The study's main advantage was its ability to process large volumes of textile waste in real-time without damaging the material, addressing a critical challenge in sustainable textile waste management. However, the study acknowledged that further optimization of the neural network model and expansion of the textile fiber database were needed for improved accuracy and real-world implementation.

In 2022, Bonifazi et al. explore the use of NIR for the automated recognition of end-of-life textile materials to support circular economy initiatives [78]. The study evaluates two different technologies (HSI and a portable spectroradiometer) for their capability to classify textile waste materials with high accuracy. The portable spectroradiometer, a compact handheld device, captures reflectance spectra from textile samples in real-time, offering a flexible and rapid method for fiber identification without requiring large-scale imaging setups. Their results indicate that both methods can successfully differentiate among cotton, silk, viscose, and various blended fabrics. To prepare the spectral data for analysis, the authors applied several preprocessing techniques, including Standard Normal Variate (SNV), Savitzky–Golay smoothing, Mean Centering, and Detrend. Using PCA and PLS-DA, the authors achieve precision rates exceeding 99.2 percent for HSI-based classification and nearly 100 percent for single-spot spectroradiometer data. The study highlights that implementing these techniques in textile-recycling plants can significantly improve material identification, reducing reliance on manual sorting and enhancing the efficiency of automated recycling operations. However, the authors acknowledge some challenges, such as the partial spectral overlap between certain textile blends, which may limit classification performance in more complex material compositions. The study suggests that expanding the dataset to include additional fiber types and blends will improve the robustness of the method. While the findings are promising, further validation on a larger scale and across diverse textile waste streams is needed before full industrial adoption.

In their 2024 study, Bonifazi et al. focused on SWIR spectroscopy and a hierarchical classification approach. This approach improved fiber differentiation by categorizing textiles based on fiber origin prior to classification of specific materials, achieving 98.4 percent precision, slightly less than the precision reported in 2022 [65]. However, the 2024 study highlights challenges in detecting textile blends, particularly viscose–polyester mixtures, whereas the 2022 method showed some limitations in distinguishing blends with high viscose content. The shift to SWIR in 2024 suggests a strategic effort to enhance classification accuracy across a wider range of textiles, but both approaches still face challenges with coatings and multi-layered structures that require further refinement for industrial implementation.

3.2. Computer-Based Data Analysis Techniques

The following paragraphs provide a brief overview of the computer-based analysis techniques integrated into the methodologies of these studies, offering essential context for understanding their role in enhancing textile waste classification. A range of classifiers to automate the sorting of textile waste is being used in selected studies. Ten articles utilized different neural network techniques such as CNN, 1D-CNN, and 1D-Inception, ANN, and

PNN. These models demonstrated strong performance in handling image and spectral data, offering flexible architectures suitable for classification tasks. All articles that used these techniques are listed under the Neural Network category in Table 5. Statistical classifiers like PLS and PLS-DA were frequently used with NIR or FTIR spectra for distinguishing fiber types. Distance-based and kernel classifiers, like SVM and kNN, proved effective in high-dimensional spaces typical of spectral datasets. Statistical classifiers, distance-based and kernel classifiers are equally used in the catalog. Tree-based models (Random Forest, Decision Trees) provided interpretable results and were used four times in the papers of catalog. Lastly, k-means clustering was used in one of the papers: this technique allowed classification without the need to label input data.

Several feature extraction and optimization methods supported the classification process. Dimensionality reduction techniques, including PCA and CVA, were applied to simplify spectral datasets. In addition, regression models such as SVR and PLS were employed to predict continuous variables such as moisture content or polyester concentration serving as precursors or complements to classification. Technical preprocessing methods such as Savitzky–Golay filtering, SNV, and EPO were used to clean and normalize spectral inputs to enhance the model robustness. A simulation-based approach using embedded photonic crystal barcodes and transfer matrix modeling was also applied to enable scalable fiber identification through optical signature analysis. Tables 5 and 6 summarize the identified techniques, the frequency of appearance, and associated studies.

Table 5. Classification techniques covered in the catalog.

Classification Techniques	Number of Appearance	Included Articles
Neural Networks	10	[8,22,56,59,60,62,70–72,77]
Statistical Classifiers	5	[62,65,76–78]
Distance-Based and Kernel Classifiers	5	[8,56,57,62,77]
Tree-Based	4	[8,61,62,77]
k-Means clustering	1	[64]

Table 6. Feature extraction and optimization techniques covered in the cataloge.

Feature Extraction Techniques	Number of Appearance	Included Articles
Dimensionality Reduction	5	[8,57,60,76,78]
Regression	2	[61,76]
Technical Preprocessing	1	[78]
Simulation/Interpretation Tools	1	[63]

Table 7 provides a summary of the 18 articles in the catalog. The studies are categorized according to their data input method (spectroscopy, imaging, or HSI) and data analysis techniques. For each study, the table summarizes the main computer-based techniques employed and reports the highest accuracy achieved as stated by the authors. The highest accuracy reported in Table 7 reflects the best-performing result from each study. Some articles presented multiple accuracy values for different models, sample groups, or testing conditions. Detailed information can be found in the review of each article mentioned in the Results Sections 3.1.1–3.1.3.

Table 7. Data input method, analyses technique, accuracy, and limitations by article.

Authors	Data Input Method	Data Analysis Technique(s)	Highest Accuracy	Limitation(s)
Liu [56]	Spec. [1]	CNN (Tr-Net) *, SVM, MLP	96.2%	Small dataset; CNN refinement needed; blend robustness limited.
Riba [57]	Spec.	PCA, CVA, kNN *	100%	No blended fabrics; contact-based sensor limits scalability.
Cura [58]	Spec.	Spectral Matching	73%	Coating, aging, thin fabrics, and blend ratios affected performance.
Li [59]	Spec.	BP-ANN	>99%	Poor results for <5% blends; excluded coated/core fibers.
Riba [60]	Spec.	CNN *, PCA, CVA	100%	Weaker performance for cotton blends; small dataset.
Qi [61]	Spec.	ATR, SVR, RF, PLSR, SPA-SVR *	$R^2 = 0.966$	Textile-specific insights limited; contamination interference; small ATR-FTIR detection area.
Du [22]	Spec.	CNN	97.1%	Blend and coated fabric confusion; reflectance issues.
Qiu [62]	Spec.	EPO, CNN, SVM, RF *, PLS	$R^2 = 0.83$	Limited to polyester–viscose blends; generalization not tested.
Iezzi [63]	Spec.	Simulation (Lumerical)	—	Only PE and nylon tested; durability and scalability untested.
Johns [64]	Spec.	k-means clustering	71%	No blend analysis; influenced by dyes and aging; moderate accuracy.
Bonifazi [65]	Spec.	PLS-DA	98.4% overall	Lower sensitivity for blends; limited surface-level detection.
Tsai [8]	Spec.	PCA, kNN, SVM, RF, ANN *, CNN	96.9%	Small dataset; dope-dyed textiles excluded; imbalanced classes.
Noh [70]	Imaging	CNN (AlexNet)	68.28%; 74.2% (clean); 53.3% (crumpled)	Garment-type classification only; no fiber analysis; low crumpled fabric accuracy.
Furferi [71]	Imaging	PNN	83.2%	Misclassified black/gray fabrics; not ideal for multicolored textiles.
Tian [72]	Imaging	CNN	>90%	No fiber detection; single garment per image; limited throughput.
Mäkelä [76]	HSI	PCA, PLS-R *	2.2–4.5% APE [2]	Small sample set; surface/layering effects caused error in outliers.
Huang [77]	HSI	CNN *, PLS-DA, SVM, RF	98.6%	Limited fiber types; blend/treated fabric generalization not assessed.
Bonifazi [78]	HSI	PCA, PLS-DA *	>99.2%	Spectral overlap in blends; limited samples; needs broader fiber variety.

[1] Spectroscopy. [2] Average prediction error. * Indicates the classifier that achieved the highest accuracy.

3.3. Metadata

The metadata section provides a structured summary of the numerical aspects of the included studies, facilitating systematic interpretation and comparative analysis of the findings. By presenting this information in tables and figures, readers can assess trends and distribution among the focal research articles.

The metadata revealed seven different publishers among the 18 articles, with Elsevier and MDPI accounting for more than 50 percent of the catalog (Table 8). Article distribution is spread across a diversity of scholarly outlets, with only three journals indicating more than one citation relevant to the review (Table 9). This journal diversity underscores the multidisciplinary nature of textile waste management research, incorporating insights from textile technology, environmental science, materials engineering, and computational methods.

Table 8. Publisher sources of 18 articles in the catalog.

Publisher	n
Elsevier	6
MDPI	5
SAGE Publishing	3
Hindawi	1
RSC Publishing	1
Wiley-Blackwell	1
Springer Nature	1

Table presents the number of sources retrieved from each library.

Table 9. Journals sorted by the number of screened articles that met this review's inclusion criteria.

Journal	n
Waste Management [79]	2
Textile Reseach Journal [80]	2
Resources, Conservation and Recycling [81]	2
Sustainability [82]	1
Sensors [83]	1
Computational Intelligence and Neuroscience [84]	1
Polymers [85]	1
Journal of Cleaner Production [86]	1
Journal of Industrial Textiles [87]	1
Analyst [88]	1
Advanced Materials Technologies [89]	1
Analytica Chimica Acta [90]	1
Applied Sciences [91]	1
Recycling [92]	1
Waste and Biomass Valorization [93]	1

A citation rate was calculated to examine articles' dissemination over time (Equation (1)). This calculation was designed to account for the passage of time to facilitate comparison of individual articles regardless of publication date (Table 10). Citation rate ranges from 0.0 to 24.4, which suggests variability among the individual articles' impact. The top two articles were published in 2020 and 2022, respectively. Citation rates were further analyzed based on methodological approach; spectroscopy, imaging, and HSI (Figure 3). HSI indicated the highest citation rate (10.99) followed by spectroscopy (8.65) and imaging (5.92). The data indicate that the selected publications are almost evenly distributed over the years, meaning the issue of automated sorting has been constantly studied in recent years (Table 11).

$$\text{Citation Rate} = \frac{\text{Citation Count}}{2025 - \text{Publication Year}} \tag{1}$$

The global textile industry relies heavily on a few key fibers, with polyester, cotton, and man-made cellulose fibers dominating global production. According to the Textile Exchange Materials Market Report 2024, polyester accounted for approximately 57 percent of global fiber production in 2023, maintaining its position as the most widely produced fiber, followed by cotton at 20 percent, and man-made cellulose fibers, which accounted for 6 percent of the total fiber market [94]. In addition to the prevalence of these individual fibers, blended fabrics are also widespread in textile production. Among the most common combinations is the polyester–cotton blend, which balances comfort, durability, and cost-effectiveness [95]. Understanding the dominance of these materials and blends is crucial for developing sustainable solutions in textile manufacturing and recycling.

Table 10. Citation count, publication year, and citation rate [1].

Article	Citation Count	Publication Year	Citation Rate [2]
Riba et al. [57]	122	2020	24.40
Du et al. [22]	65	2022	21.60
Cura et al. [58]	71	2021	17.75
Mäkelä et al. [76]	70	2020	14.00
Huang et al. [77]	37	2022	12.33
Liu et al. [56]	46	2020	9.20
Sun-Kuk Noh [70]	33	2021	8.25
Tian et al. [72]	7	2024	7.00
Li et al. [59]	27	2021	6.75
Riba et al. [60]	20	2022	6.66
Qi et al. [61]	18	2022	6.00
Bonifazi et al. [78]	20	2022	6.66
Bonifazi et al. [65]	6	2024	6.00
Johns et al. [64]	3	2024	3.00
Furferi et al. [71]	5	2023	2.50
Iezzi et al. [63]	4	2023	2.00
Qiu et al. [62]	1	2023	0.50
Tasi et al. [8]	0	2024	0.00

[1] These data are captured as of 9 May 2025. [2] refer to Equation (1).

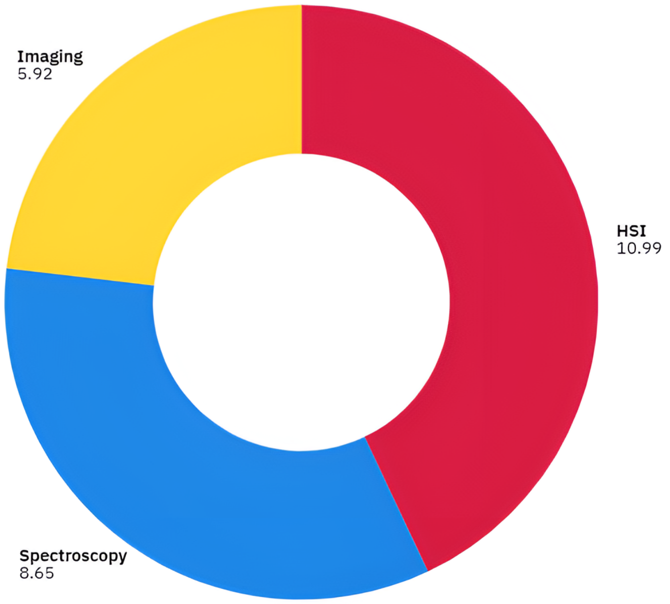

Figure 3. Average citation rate by method.

Table 11. Published articles' year distribution.

Published Year	n
2020	3
2021	3
2022	5
2023	3
2024	4
Total	18

Figure 4 shows the distribution of pure fibers covered in this review, with cotton, wool, and polyester most commonly analyzed. This aligns with the Textile Exchange Materials Market Report 2024 [94], which identifies polyester and cotton as the most widely used fibers globally. The prominence of these fibers highlights the potential need for effective recycling solutions. Overall, this review found that the materials investigated across the 18 selected articles can be categorized into four main fiber groups. Within each group, the most prominent materials are polyester, nylon, and acrylic for synthetic fibers; cotton, wool, and silk for natural fibers; polyester/cotton, polyester/viscose, and polyester/nylon for blended fibers; and viscose, lyocell, and acetate for man-made cellulose fibers.

Despite this general alignment, certain gaps and underrepresented areas emerge when comparing global production data with research coverage. On the one hand, the heavy focus on polyester and cotton, both as pure fibers and in blends, reflects their dominant role in the industry and the urgent need to improve automated sorting and recycling processes for these materials. Due to their significant dominance in the global textile market and the ongoing challenges associated with recycling products made from these materials, it is crucial for academic research to remain focused on these types of fiber. This will enable the development of scalable and effective solutions to mitigate their environmental impact. On the other hand, polyamide (nylon), the second-most used synthetic fiber, accounted for 6.7 million tonnes and 5 percent of the global fiber market in 2023 [94], yet appears less frequently in reviewed studies (referring to the Figure 4) despite its significant role in synthetic and blended textiles.

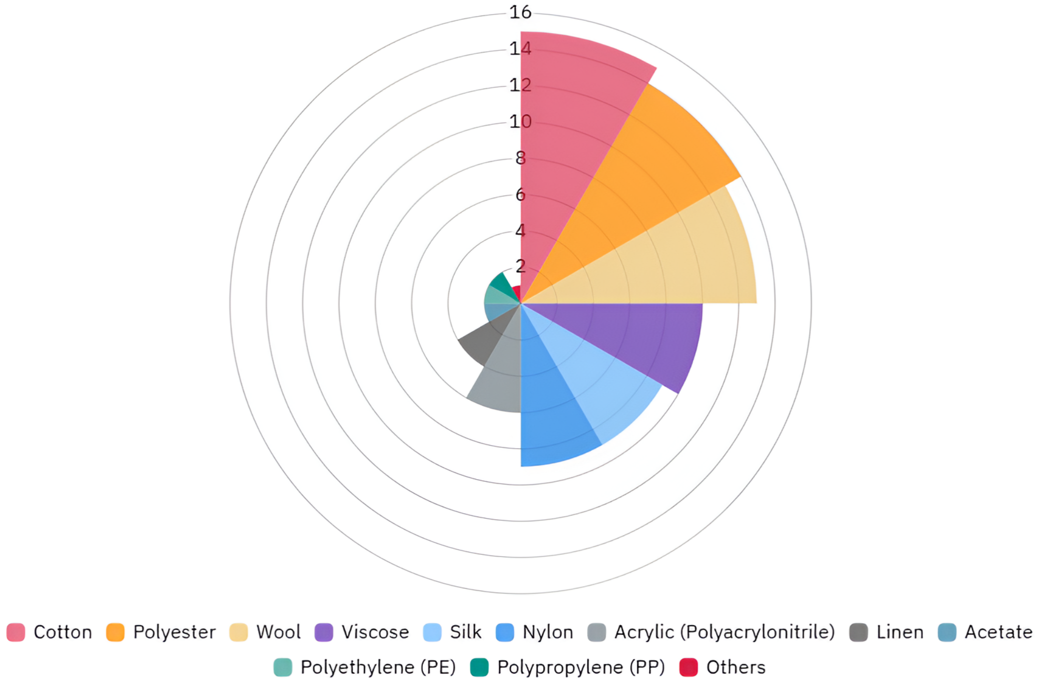

Figure 4. Distribution of pure fiber types analyzed in the review paper, illustrating the frequency of each material's occurrence in textile-recycling studies.

4. Discussion

The findings highlight the growing potential of computer-based technologies in textile waste sorting, with neural networks, statistical classifiers, distance-based, and kernel classifiers emerging as the leading techniques. Spectroscopy-based approaches, including ATR-FTIR, NIR, SWIR, Raman, and autofluorescence spectroscopy, have demonstrated significant advancements when integrated with ML and DL techniques, offering improved accuracy in textile classification. However, persistent challenges remain, particularly in the classification of blended fabrics, which are major obstacle across all reviewed spectroscopy-based systems. While DL models such as CNNs and BP-ANNs have enhanced classification accuracy, external factors like fabric coatings, aging effects, and moisture continue to introduce notable inaccuracies. Imaging-based methods, while effective in classifying textiles based on visual attributes such as color, shape, and type, struggle with material-level differentiation, which is essential for effective recycling. Issues related to image quality, garment deformation, and the rigidity of predefined classification categories further limit their effectiveness. Similarly, while HSI techniques provide a non-destructive and high-throughput alternative for fiber identification, they face difficulties such as spectral overlap in fiber blends, dataset limitations, and a reliance on computationally intensive calibration.

These challenges emphasize the urgent need for larger and more comprehensive datasets to enhance model training, reduce issues such as overfitting, and enable the development of more industrially scalable solutions. The lack of sufficiently diverse and standardized datasets not only impacts the generalizability of existing models but also hinders their transition to large-scale industrial applications. Thermal methods, though occasionally explored for textile analysis, were excluded from this review due to concerns regarding their scalability, potential speed limitations in high-throughput settings, and their often-destructive nature, which can alter fabric integrity and hinder subsequent recycling. These factors limit their applicability in industrial environments where non-destructive and rapid classification is essential.

A critical limitation across all reviewed technologies is their inability to accurately classify coated, dyed, or aged textiles, which introduces notable classification errors in real-world applications. While preprocessing techniques have been explored to mitigate these inaccuracies, they may not be sufficient on their own. Further research should explore more sophisticated preprocessing strategies, integrative learning frameworks, or adaptive ML techniques to improve robustness in challenging textile conditions. Another overlooked aspect in the field is the limited adoption of more efficient DL architectures that have proven successful in other domains. Future research should investigate methods such as Graph Neural Networks or self-supervised learning models that could potentially enhance classification accuracy while requiring fewer labeled training examples. Additionally, the integration of hybrid methodologies, such as combining spectral and imaging-based techniques or incorporating thermal analysis into existing frameworks, could enhance textile-sorting performance by leveraging complementary data sources. Nylon, despite its five percent global market share [94], deserves more attention in textile-sorting research. The fiber's underrepresentation among research may be due to spectral similarity with other synthetics, limited research focus, or a lack of well-annotated datasets. Finally, to truly industrialize these methods, researchers should explore strategies that encompass the entire textile supply chain, developing commercializable solutions that incorporate systematic tracking and sorting mechanisms. Establishing a standardized and automated information-sharing framework between textile manufacturers, recyclers, and policymakers could pave the way for a more efficient, traceable, and scalable textile waste management ecosystem.

5. Conclusions

This review underscores the growing efficacy of computer-based methods in textile waste sorting; however, it also reveals significant limitations that must be addressed before these technologies can be industrially scaled. Addressing this gap through expanded research efforts will be essential to create more comprehensive waste management systems capable of handling both conventional fibers and more complex, multi-material combinations. Overall, aligning academic research priorities more closely with the material mix seen in global production and waste streams will be crucial to building an effective and sustainable circular textile economy. One of the most persistent challenges across all reviewed methodologies, particularly spectroscopy-based systems, is the accurate classification of blended fabrics. This difficulty stems not only from the overlapping spectral signatures of different fibers but also from structural complexities; such as cases where one fiber envelops another (e.g., core-sheath yarns), obscuring its spectral signal. These intricacies are particularly problematic in NIR- and FTIR-based systems; which often analyze only surface-level characteristics.

Compounding this issue are external variables like fabric coatings, moisture, and aging, which introduce variability into the spectral data and reduce classification reliability. Current preprocessing techniques like SNV and EPO indicate progress in reducing this noise; however, these measures are insufficient when applied to highly variable real-world textile waste streams. To address this, future work should focus on developing blend-sensitive classification models, possibly through adaptive learning algorithms or multi-modal architectures that integrate spectral and visual data.

The lack of comprehensive, diverse datasets remains another key bottleneck. Small datasets limit generalizability and exacerbate overfitting, particularly in DL models. Expanding datasets to include more fiber types, blends, surface treatments, and aged textiles will be critical for improving model robustness and real-world applicability. Furthermore, exploring advanced CNN architectures or alternative models such as self-supervised or graph-based learning could allow for higher accuracy while reducing the dependency on large labeled datasets.

In the case of imaging-based systems, their strength in identifying shape and color is often offset by an inability to distinguish fiber composition; integrating imaging techniques with spectroscopy, or including additional modalities like thermal or mechanical sensing, could lead to a more holistic and accurate textile classification framework. For instance, a hybrid approach combining NIR spectroscopy with HSI, as discussed in this paper, improved classification accuracy. To advance toward practical implementation, future research must prioritize the development of scalable, adaptable, and integrative frameworks that address current technical limitations. Such efforts are essential to enable reliable, industry-ready textile waste-sorting systems that support a circular and sustainable economy.

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Abbreviations

The following abbreviations are used in this manuscript:

PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PSALSAR	Protocol, Search, Appraisal, Synthesis, Analysis, and Reporting
EPA	Environmental Protection Agency
AI	Artificial Intelligence
ANN	Artificial Neural Network

CE	Circular Economy
SLR	Systematic Literature Review
DOI	Digital Object Identifier
Q1-4	Journal Quality Quartiles
RGB	Red, Green, Blue
DL	Deep Learning
CV	Computer Vision
SWIR	Short-Wave Infrared
ATR	Attenuated Total Reflectance
FTIR	Fourier Transform Infrared
HSI	Hyperspectral Imaging
NIR	Near-Infrared spectroscopy
ML	Machine Learning
kNN	K-Nearest Neighbor
CNN	Convolutional Neural Network
RF	Random Forest
PCA	Principal Component Analysis
CVA	Canonical Variate Analysis
Tr-Net	Textile Recycling Net
BP-ANN	Backpropagation Artificial Neural Network
SVM	Support Vector Machine
PLS	Partial Least Squares
IoT	Internet of Things
PNN	Probabilistic Neural Network
EPO	External Parameter Orthogonalization
1D-CNN	One-Dimensional Convolutional Neural Network
1D-Inception-CNN	One-Dimensional Inception-based Convolutional Neural Network
SPA	Successive Projections Algorithm
SVR	Support Vector Regression
R^2	Coefficient of Determination
PhC Fibers	Photonic Crystal Fibers
PMMA	Polymethyl Methacrylate
PE	Polyethylene
FDTD	Finite-Difference Time-Domain
PLS-DA	Partial Least Squares Discriminant Analysis
RAL	Reichs-Ausschuss für Lieferbedingungen
SNV	Standard Normal Variate
k-means	K-means clustering
MLP	Multi-Layer Perceptron
GS	Google Scholar

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