

Chapter

AI-Driven Apparel Image Retrieval and Feature Optimization for Smart and Sustainable Textile Manufacturing

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Abstract

In response to mounting environmental challenges, excessive resource use, and the rapidly increasing volume of textile waste, the global textile and apparel sector is accelerating its transition toward digital transformation to achieve greater efficiency, sustainability, traceability, and intelligent manufacturing practices. Artificial intelligence (AI) has emerged as a highly transformative enabler for smart and sustainable textile systems, particularly through the use of computer vision, machine learning and deep learning technologies. These advanced methods allow automated inspection, classification, retrieval, and decision-making processes across textile production and post-consumer waste management systems. This chapter significantly extends a previously published research article on apparel image retrieval using a modified AlexNet architecture integrated with Mish activation functions and optimized feature selection through Joint Shannon's Entropy and Pearson Correlation Coefficient (JSE-PCC). The original study focused on improving retrieval performance and classification precision for fashion image datasets. In this chapter, the work is reframed within the broader context of sustainable textile manufacturing, and circular economy initiatives demonstrating how AI-driven image retrieval systems can support material reuse, automated garment sorting, quality control, defect detection, inventory digitization, and intelligent production cycles. By improving retrieval accuracy and reducing computational overhead, the proposed framework contributes directly to waste reduction, energy efficiency, resource optimization, and circular fashion workflows. This chapter bridges research findings with real-world industrial textile applications, showing how AI-based apparel recognition and retrieval technologies can power next-generation digital textile ecosystems, promote sustainable innovation, and strengthen resilience in the future global fashion supply chain.

Keywords: sustainable textile technology, apparel image retrieval, feature optimization, resource-efficient AI, smart manufacturing, AI-driven fashion systems

1. Introduction

Existing modes of textile production are increasingly misaligned with present-day expectations, as pressures related to resource stewardship and operational effectiveness continue to intensify. This transition is further driven by growing global demand, escalating manufacturing costs, and increasingly strict environmental regulations, which compel manufacturers to move away from conventional labor-intensive and linear production approaches. Textile production systems that follow a one-directional flow from raw material extraction to disposal inherently fail to retain material value, leading to excessive resource loss and limited recovery of used textiles. A substantial share of apparel exits the market prematurely due to excess production planning, market mismatch, quality inconsistencies, and rapid shifts in style demand. Manual inspection, sorting, and quality assessment in textile processing are highly labor-dependent, prone to variability, and challenging to scale, often resulting in reusable or recyclable textiles being incorrectly directed to landfills or incineration.

Similarly, detecting defects at later stages of production significantly amplifies material waste, energy usage, and the cost of reprocessing. Conventional analytical approaches struggle to extract timely insights when confronted with large-scale, heterogeneous multimedia data [1]. Comparatively, artificial intelligence (AI) provides powerful data-driven decision-making capabilities when analyzing large-scale datasets. The ability of machines to visually perceive and interpret apparel-related data is changing how fashion systems function, from design decisions to operational execution. This growing integration of AI technologies has gained substantial attention in recent decades.

Unlike old traditional techniques, which rely on the manual formulation of coding procedures, AI provides powerful mechanisms for understanding and analyzing complex image semantics through repetitive learning and powerful computerized tasks. Textile practices are being reorganized as computational reasoning and automated intelligence begin to influence how products are conceived, processed, assessed, and returned to material circulation. Textile manufacturing today is guided less by fixed automation rules and more by systems that can sense, interpret, and reason over visual and operational data in real time.

Among these technologies, AI-driven image analysis and apparel image retrieval have emerged as powerful tools that enable machines to identify, classify, and track garments across the entire production and lifecycle continuum [2]. Generally, the steps involved in a query-based image retrieval system include feature extraction, feature description, feature engineering, and feature similarity measurement. Optimization at each stage is required to strengthen the performance of apparel retrieval. The general flow followed by retrieval approaches is depicted in **Figure 1**. By transforming visual information into meaningful and actionable knowledge, image retrieval systems establish the basis for intelligent production cycles that emphasize efficiency, sustainability, and circular manufacturing practices.

Figure 1 illustrates the end-to-end workflow of AI-driven image retrieval for smart and sustainable textile manufacturing, showing how visual intelligence is embedded throughout the textile lifecycle. The process begins with garment and fabric image capture from production lines, warehouses, and recycling centers, creating a unified visual data source. These images can be processed using our proposed M-AlexNet, enabling robust extraction of texture, shape, color, and

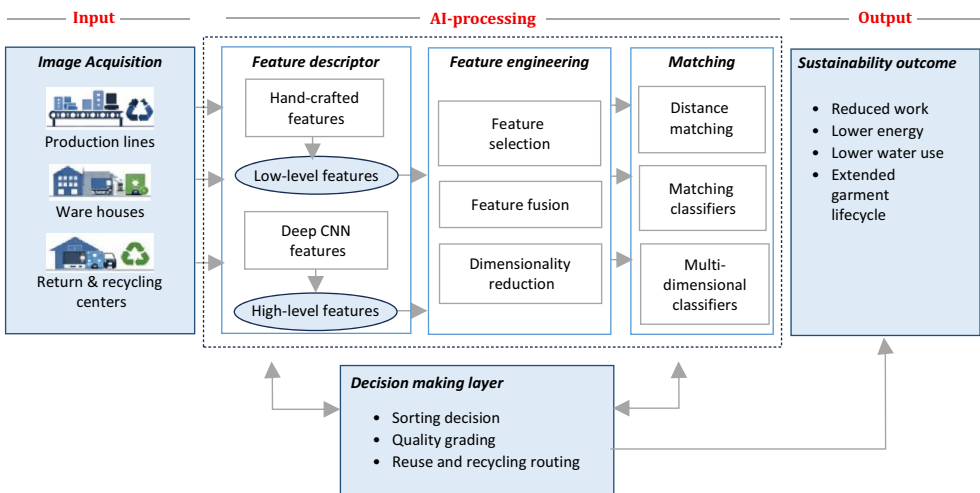


Figure 1.
Process of AI-based apparel retrieval in the textile industry.

pattern features. To improve efficiency and retrieval accuracy, feature optimization is performed to retain informative features and remove redundancy. These optimized feature vectors are used to measure visual similarity via Euclidean distance, facilitating accurate identification of visually related garments. The outcomes of visual matching inform task-dependent actions, enabling systems to automatically separate items, flag imperfections, assign quality levels, and determine whether garments should be circulated again, refurbished, or broken down for material recovery. Once these determinations are made, they influence how the factory adapts – altering how goods are tracked, how output is scheduled, and how limited resources are strategically deployed. Finally, the workflow delivers key sustainability outcomes such as waste reduction, improved energy efficiency, and the enablement of circular fashion, with a feedback loop that continuously updates the image database and production planning systems to support adaptive, demand-aware, and sustainable textile manufacturing.

When sustainability principles guide manufacturing workflows, AI-driven visual matching becomes central to deciding which garments can reenter use cycles and how they should be mechanically sorted. Conventional garment separation depends largely on human judgment – a practice that limits throughput, introduces variability, and cannot keep pace with high-volume textile streams. Learning-based visual matching systems allow machines to recognize related apparel items and textile elements on their own, making it possible to sort products into appropriate circulation, refurbishment, or material recovery routes with high efficiency. By preserving the usability of textile resources, these systems prevent premature disposal and encourage continued material participation within closed production loops.

The contribution of AI-driven image retrieval extends further into waste reduction and resource optimization. The ability to accurately interpret garment condition and structure enables manufacturers to eliminate unnecessary processing steps and restrain surplus output. Efficient extraction of fine-grained visual features helps reduce material, water, and energy consumption and enables manufacturers to reuse existing designs and materials. This data-oriented approach facilitates

AI-supported planning, early condition-aware tactics during maintenance, and autonomous production in smarter textile manufacturing systems.

Visual matching systems enable ongoing machine-based observation throughout manufacturing operations, allowing product quality to be assessed and maintained without interruption. Identifying fabric defects at later stages of the production cycle in conventional quality inspection methods leads to increased material waste, higher recycling requirements, and elevated energy consumption. Finding problems early changes how factories work – materials are not wasted, and quality becomes something the system enforces on its own instead of being manually checked later [3].

At the core of these capabilities lies the advancement of deep learning-based feature representation and optimization. Initial garment retrieval approaches depended on manually designed visual descriptors that struggled to remain reliable when exposed to the variability and noise of real industrial environments. Modern convolutional architectures excel at capturing detailed visual information, yet the resulting feature sets are frequently bloated, redundant, and costly to process. Addressing this challenge is essential for deploying retrieval systems in real-time, resource-constrained manufacturing environments.

This chapter builds upon the previously published research titled “Clothes Retrieval using M-AlexNet with Mish Function and Feature Selection using Joint Shannon’s Entropy Pearson’s Correlation Coefficient” [4]. By altering how the network responds to visual patterns and discarding unnecessary descriptors, the method achieved better retrieval results without increasing computational load. In this chapter, that research is extended beyond algorithmic performance to illustrate its relevance within intelligent production cycles, automated quality control, waste reduction strategies, resource optimization, and circular fashion workflows.

By reframing the proposed AI-based apparel image retrieval framework within the broader context of digital transformation and sustainable textile manufacturing, this chapter highlights how optimized deep learning models can function as enabling technologies for next-generation textile systems. Findings indicate that visual retrieval technologies operate as an enabling layer for coordinated, resource-aware textile operations, extending far beyond basic image matching.

2. M-AlexNet-based apparel retrieval framework

The textile industry is under significant pressure in fabric sorting, pattern, color, and design matching, cataloging, quality control, recycling, waste reduction, and recommendation systems [1]. When prior apparel designs can be intelligently reused through automated retrieval, development shifts away from material-heavy prototyping toward digital reuse, cutting down both resource consumption and production energy demands. By enhancing visual similarity assessment as a fundamental function, the proposed method establishes a scalable basis for subsequent applications, including automated inspection and adaptive production workflows. This direction mirrors modern manufacturing paradigms in which intelligent systems translate visual observations into concrete process-level actions.

Our proposed research focuses on the problem of apparel image retrieval, which simply means enabling a computer system to find apparel items that look similar to a given image from a very large collection of apparel photographs. For example, when a picture of a shirt, dress, or jacket is provided, the system should be able to

search through thousands or even millions of images and identify garments with similar appearances. This task is much more complex than it sounds because apparel does not always appear the same in different images. A single garment can look very different depending on whether it is worn by a person, displayed on a mannequin, folded on a table, or hung in a store. These visual differences make it difficult for computers to recognize that two images represent similar apparel items.

Under real-world operating conditions, numerous factors introduce additional complexity to apparel image retrieval. For example, lighting conditions can vary widely, making colors appear brighter, darker, or slightly different. The background of the image may contain other objects, people, or scenery that distract the system from focusing solely on the apparel item. The pose of the garment, such as whether it is viewed from the front, side, or at an angle, also changes its appearance. While natural and woven fibers form the basis of automated garment identification, differences in their tactile and visual structure significantly complicate pattern discrimination. All of these variations reduce retrieval accuracy and make it difficult to match garments reliably in practical settings such as online retail platforms, warehouse sorting systems, or factory-level inventory management [5].

In earlier methods, visual features were manually engineered rather than learned through modern representation learning techniques. These are manually designed rules that describe certain visual characteristics of an image. When examined at its most granular scale, visual data is formed through the interaction of chromatic information, structural contours, and surface patterns. The distribution of color values from low to high pixel levels quantifies image intensity, texture describes the surface and structural properties of objects within an image, and shape represents the outlines and geometrical forms of objects. Various algorithms or processes are used to quantify the color, shape, and texture of an image, aiming to represent color intensity, capture object silhouettes, and characterize surface properties such as smoothness or coarseness, respectively. These algorithms are comparatively fast and do not require much computational power but still have some limitations. For instance, if the image is captured in real-time, uncontrolled environments, then these handcrafted algorithms cannot adapt well to variable lighting conditions, different backgrounds, or viewing angles.

In response to these difficulties, modern learning systems rely on layered perception models that construct visual understanding autonomously by extracting structure and patterns from raw observations. By mirroring how people visually interpret their surroundings, these systems derive distinguishing patterns without relying on manually engineered inputs. The color, shape, and texture information of apparel images captured in real-world textile environments can be automatically learned by pretrained networks, making them more robust to variations in lighting, background, and viewpoint. Despite their strong performance gains, deep learning approaches bring additional challenges in terms of computational complexity and processing efficiency.

The use of deep learning approaches for apparel retrieval extracts features with very large dimensionality, making processing and feature handling more challenging. During processing, an image is transformed into numerical values known as a feature vector, which serves as the representation that a computer can interpret. Within these complex and high-dimensional feature vectors, some numerical values are informative, while others are irrelevant or redundant for distinguishing garments. As the size of the feature vector increases, memory

requirements and computational costs grow significantly, creating performance bottlenecks in large-scale garment image retrieval systems [6].

To address these challenges, a modified deep learning architecture, referred to as modified AlexNet (M-AlexNet), is proposed based on the well-established AlexNet model. AlexNet belongs to an early generation of deep visual learning systems whose internally learned patterns continue to support machine interpretation of images across many application domains. The modification introduced in M-AlexNet focuses on improving how the network processes information internally. Specifically, the commonly used activation function, called rectified linear unit (ReLU), is replaced with a newer activation function known as Mish. An activation function controls how information flows through the network and determines which signals are strengthened or weakened during learning.

The ReLU is popular because it is simple and fast, but it has limitations. It completely removes negative values, which can cause certain parts of the network to stop learning altogether – a problem often referred to as “dead neurons.” Mish enables a smooth and continuous flow of both positive values and small negative responses through the network, supporting richer feature learning. This smoother behavior helps the network learn more detailed and subtle patterns, which is especially important for fabric images where fine texture details, stitching patterns, and fabric structures matter. Consequently, the M-AlexNet model has a greater capability to effectively learn fine-grained details from garment images [4].

During learning, the network refines its internal representations using a probability-driven output mechanism that assigns each apparel item to the most plausible class. Prior to learning garment-specific characteristics, the model acquires broad visual knowledge by being exposed to a widely used benchmark collection of everyday images, namely CIFAR-10. This dataset contains a wide variety of everyday objects and helps the network learn basic visual concepts such as edges, shapes, and color patterns. This process, known as pretraining, gives the model a strong starting point and improves its ability to learn more specialized fabric-related features later on [4].

Even with improved feature extraction, the problem of high-dimensional data remains. To further optimize the system, a feature selection technique is introduced that combines two statistical measures: Joint Shannon’s Entropy and Pearson’s Correlation Coefficient (JSE-PCC). The first is Shannon’s entropy, which measures how much useful information a particular feature contains. Visual descriptors that exhibit greater variability carry stronger distinguishing power, making them more effective for separating garment images. The second measure is Pearson’s correlation coefficient, which evaluates how similar one feature is to another. Features that behave almost identically usually repeat the same information rather than improving distinction.

By combining these two measures, the proposed method ranks features based on both their importance and uniqueness. Only the most informative and least redundant features are selected, while unnecessary ones are removed. This significantly reduces the size of the feature vectors without compromising retrieval performance. This leads to a more efficient framework with faster execution and lower storage demands, enabling real-time operation in industrial-scale environments, including textile plants, sorting centers, and smart warehouses.

To test whether the method works beyond controlled settings, it was applied to several independent collections of garment images, allowing performance to be examined across different visual conditions. Testing shows that when M-AlexNet is

combined with the refined feature selection approach, the system identifies garments more reliably than many conventional neural models. It achieves higher accuracy while using fewer computational resources, proving that careful network design and feature optimization can significantly improve retrieval performance.

On DeepFashion2, the M-AlexNet with Mish achieved an accuracy of 85.15%, exceeding the baseline by 5.11%. Similar performance gains were observed on the multiview clothing (MVC) (82.04%, + 1.95%) and cow images dataset (CID) (83.65%, + 3.51%) datasets. These results demonstrate that integrating improved activation dynamics with feature selection significantly enhances retrieval accuracy while reducing computational overhead [4].

Although the primary focus of this research is apparel image retrieval, the significance of this research extends far beyond standard academic performance measures. Cutting-edge apparel retrieval systems simplify automated garment sorting, identification of reusable fabric materials, and intelligent digital inventory control. The performance of these functionalities plays a key role in textile manufacturing systems designed to achieve efficient resource optimization, waste reduction, and the promotion of circular fashion models. By more effectively improving apparel matching performance, this research contributes to intelligent production systems that align with sustainability objectives and the broader vision of digital transformation in the textile industry.

3. Industrial applications of AI-driven apparel image retrieval in sustainable textile manufacturing

AI-powered apparel image retrieval facilitates cutting-edge textile manufacturing applications throughout both production and postproduction phases. The **Figure 2** illustrates the central role of AI-based apparel image retrieval as a unifying visual

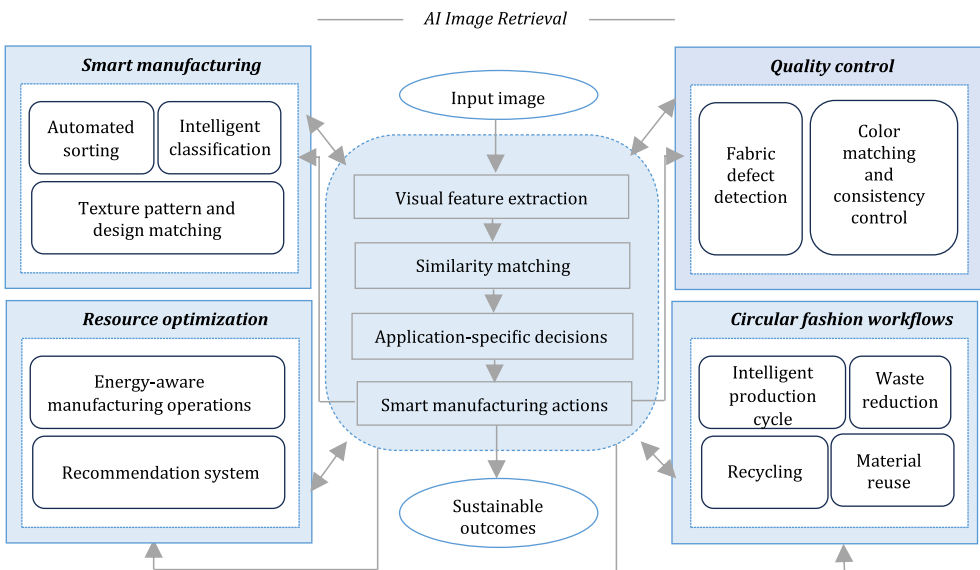


Figure 2.
Applications of apparel retrieval in the textile industry.

intelligence layer across the textile industry. The central retrieval engine learns and processes key attributes such as color distributions, textures, structural shapes, and design patterns from textile images, supporting quality control through automated defect detection, identification of recurring fault patterns, and verification of color consistency, thereby reducing reliance on manual inspection. Proactive defect detection facilitates prompt corrective actions and helps prevent defects from propagating across large-scale production batches. This leads to lower material waste, an efficient production process, and elevated manufacturing quality. By accurately recognizing and monitoring garments, this visual intelligence supports better organization of inventory and informs predictions for supply and demand across storage and sales networks.

The illustration also demonstrates that leveraging AI for visual analysis extends its impact beyond manufacturing lines, supporting sustainable workflows and facilitating the reuse and recycling of garments. Within smart textile manufacturing systems, textiles with similar material types, fabric textures, design patterns, and quality conditions are identified by intelligent retrieval systems, enabling automated sorting and optimized resource utilization based on real-time visual data. In support of circular fashion, the platform determines the category and material quality of garments, enabling textiles to be systematically redirected for reuse, resale, or material recovery at the end of their lifecycle. As a unifying capability, intelligent apparel analysis underpins multiple industrial functions, enabling production systems to operate efficiently while adhering to sustainability principles. Accurate garment identification, enabled by modern technologies such as the internet of things, blockchain, and AI-driven systems, supports efficient processing and contributes to sustainable textile production by reducing manual effort, enhancing operational efficiency, minimizing material waste, and advancing circular economy practices across the entire textile lifecycle [7].

3.1 Role in smart and sustainable textile manufacturing systems

Modern textile production depends on intelligent machines that observe the factory environment, make sense of what they detect, and act accordingly to maintain smooth operations. By streaming and analyzing data in real time, the platforms support ongoing oversight and more precise operational evaluation. As a result, these systems are well-prepared to respond efficiently to dynamic functioning environments and intelligently manage resources without human intervention across warehousing and distribution operations. By processing and understanding visual cues, these systems can sort and analyze apparel independently, establishing the core capability for next-generation textile production.

Under the Industry 4.0 paradigm, real-time data acquired from industrial sensing and actuation infrastructures is used to assess operational performance and trigger appropriate actions through perception, decision-making, and action feedback loops. These system-driven actions, such as AI-assisted sorting and intelligent classification, enable efficient handling of garments based on their visual characteristics and support prompt, data-driven decisions to automatically route apparel and textile materials to appropriate pathways according to their visual condition. These types of systems are more flexible and responsive, thereby minimizing delays and resource waste, and

enabling textile operations to continuously improve performance without heavy reliance on manual inspection.

In the textile manufacturing process, sustainability is accomplished by reducing waste material and landfill deposition, cutting down carbon discharge and production costs through the efficient use of energy during the progression of spinning, weaving, dyeing, and finishing, and by extending the product life cycle of garments by focusing on durable designs, quality assurance, and effective recycling. One of the significant constraints in achieving sustainability goals is the misclassification of apparel based on fabric composition, quality attributes, or category, which frequently results in unnecessary waste instead of recovery for reuse or recycling. Mitigating these challenges is essential for improving material utilization by accurately recognizing garments, continuously assessing their condition, and routing them across different stages of their lifecycle [7].

3.1.1 Automated sorting and intelligent classification

Contemporary, sustainability-focused textile factories depend on automated, AI-based sorting and classification to manage high production volumes with precision and speed. Labor-intensive garment sorting demands substantial labor and processing time, places heavy strain on resources, and frequently leads to uneven results, particularly when dealing with similar-looking apparel or blended textile streams. Automated sorting refers to the use of mechanical systems and sensing technologies, supported by operational control frameworks, to automatically organize and classify garments into specific categories based on garment type, quality condition, or reuse viability [2].

Smart classification systems go further than traditional sorting by learning patterns in data and using them to make reliable categorization decisions. With continuous data accumulation, the system becomes more accurate over time and better able to adjust to changes in materials and production environments. An intelligent retrieval system enhances automated sorting and classification by using AI-driven algorithms to efficiently search, identify, and retrieve relevant items or information. Through instantaneous data capture from machines and heterogeneous sensors, image-based retrieval supports rapid garment identification and efficient redirection of materials toward reuse, recycling, or disposal pathways [8].

3.1.2 Textile pattern and design matching

The AI-based image retrieval helps textile factories accurately detect and match fabric patterns, improving both precision and productivity. Textile patterns, including prints, decorative motifs, jacquard structures, embroidery layouts, and culturally inspired textile designs, are visually intricate, making manual comparison against large design repositories time-consuming, subjective, and error-prone. By harnessing automation, these systems facilitate the swift and precise recognition of similar textile patterns, thereby supporting creative and original workflows while ensuring operational efficiency.

After acquiring detailed textile imagery, the data undergoes multiple conditioning stages, such as artifact removal, scale and orientation adjustment, and structural correction, to ensure consistency for subsequent analysis. Subsequent

visual features are extracted via traditional or deep learning-based models to discern complex structural patterns and fine-grained inter-pattern variations. These features are encoded as indexed feature vectors, enabling efficient similarity assessment through distance metrics (e.g., Euclidean or cosine), with advanced frameworks incorporating pattern alignment to preserve motif continuity. Collectively, this technical framework ensures high-accuracy, automated, and scalable textile pattern recognition and matching, supports process quality monitoring, enables design reuse, and promotes sustainable textile practices.

3.2 Intelligent quality control and inspection

Textile inspection processes increasingly rely on autonomous analytical platforms capable of evaluating material soundness and adherence to specifications across the full production workflow.

Conventional textile inspection, largely dependent on manual evaluation, often suffers from variability, limited scalability, and slow throughput, while intelligent quality control frameworks leverage advanced sensing technologies and AI-based analytics to achieve reliable, uniform, and rapid defect identification in contemporary manufacturing environments. The deep network-driven content-based apparel retrieval architecture mitigates intrinsic process inefficiencies and is adaptable across diverse textile manufacturing stages – ranging from fabric engineering to surface finishing – thereby ensuring standardized quality conformance while curtailing manual oversight and operational expenditure [9].

From a technological standpoint, modern quality inspection solutions leverage perceptual vision modules, computational image interpretation, and adaptive learning mechanisms, supported by high-fidelity optical acquisition, to analyze textile surface attributes. The sensor-acquired data are subsequently processed for noise suppression, photometric normalization, and feature registration, thereby enabling instantaneous quality assessment. Feature extraction techniques – such as texture analysis, edge detection, and color consistency measurement – are used to identify defects including holes, stains, misprints, broken yarns, and pattern distortions. Contemporary compliance verification paradigms exploit neural network architectures to support self-adaptive learning of representative feature constructs. These architectures particularly adopt convolutional neural network (CNN) architectures to capture complex texture patterns, transform them into meaningful feature representations, and accurately classify multiple defect categories. Model performance is progressively strengthened because of repeated model training and incremental learning [10].

3.2.1 Color matching and consistency control

Color standardization and uniformity enforcement ensure that all woven and knitted fabrics, raw fibers, and finished products maintain consistent hue and saturation in accordance with predetermined design specifications across successive production lots. Achieving accurate color outcomes demands faithful replication of target shades while preserving uniform appearance across production runs, even as fabric types, dye sources, machinery, and environmental conditions fluctuate. Conventional methods exploit handcrafted evaluation techniques, which fail to capture the complex features from color-texture characteristics. Ensuring consistent color precision and shade harmony is crucial in fabric production,

as even minimal inconsistencies may degrade garment standards, erode company image, and trigger batch refusals, customer dissatisfaction, and costly corrective measures.

Leveraging high-resolution imaging and sophisticated sensing technologies, AI-powered frameworks acquire detailed color representations from garment data, effectively capturing intricate textures and tonal variations while achieving elevated precision and recall. Machine learning algorithms, including CNNs and other deep learning models, analyze color and texture data to detect subtle variations, predict potential deviations, and recommend optimal dye formulations that may elude human observation. The smart systems continuously monitor sensor data, control color formulations, limit waste, and ensure consistent quality throughout the textile production life cycle [10].

3.3 Resource optimization

The apparel production sector represents a high-input manufacturing ecosystem characterized by extensive consumption of yarn material, chemical pigments, water resources, power requirements, and human labor across all stages of the production lifecycle, incorporating spinning processes, textile formation processes, chromatic processing, functional finishing stages, and apparel assembly processes. A strategically engineered allocation of material assets and utility resources across textile production pipelines facilitates the simultaneous reduction of environmental load and enhancement of cost-effectiveness. Precision-driven resource optimization minimizes material waste and reprocessing while maximizing process efficiency, ensuring the long-term sustainability and economic feasibility of manufacturing systems.

The AI ecosystems synthesize large-scale operational intelligence from sensing, production, and inspection layers to identify inefficiencies while leveraging machine learning to forecast material demand, optimize cutting strategies, and regulate energy–water consumption in coloration and finishing stages. By anticipating demand with predictive intelligence, production systems can align resources precisely with actual needs rather than speculative output [11].

The AI-supported optimization systems originate from the structured acquisition of production and environmental data, which is refined and processed by predictive and adaptive learning algorithms such as regression, neural, or reinforcement learning models. The models systematically examine correlations between process settings and resource expenditure to infer optimal operating regimes. Utilizing model forecasts, the platform self-adjusts machinery configurations, refines production coordination, and executes corrective interventions instantly. Through feedback-driven iterative learning, intelligent systems progressively evolve, thereby reducing material waste, lowering energy and water consumption, enhancing process efficiency, and fostering a more sustainable textile manufacturing ecosystem.

From a process engineering perspective, precise visual retrieval optimizes the deployment of garment and fabric stocks. Dependable detection and pairing of garments with comparable visual characteristics enable industrial processes to prioritize reintegration, reconditioning, and secondary manufacturing, minimizing reliance on fresh raw materials and the associated environmental and operational resource expenditures. As a consequence, material throughput optimizes performance and harmonization of manufacturing methodologies [11].

3.4 Circular fashion workflows

Closed-loop fashion circularity infrastructure aims to preserve apparel value by endorsing refurbishment, re-marketing, circular use, and resource reclamation. Such workflows prioritize the prolonged utility of apparel by channeling products through successive value-retention pathways – including restoration, secondary circulation, reprocessing, and material recovery – thereby substantially reducing material loss and ecological impact. A primary challenge in deploying these workflows at an industrial scale is the absence of automated systems that can reliably detect and classify garments throughout their various lifecycle phases.

In the absence of accurate identification, garments may be incorrectly sorted or discarded too early, hindering efforts to promote a circular economy. By leveraging AI-based image retrieval, the system ensures accurate and continuous recognition of garments throughout their entire lifecycle, addressing challenges in automated textile management.

Circular fashion systems are generally initiated at the design stage through approaches that emphasize long-term functional resilience, end-of-life material recoverability, and systematic tracking of constituent resources. At the production stage, the strategic regulation of material and energy flows, together with continuous operational oversight, helps suppress quality inconsistencies and prevent avoidable resource loss.

Following the use phase, apparel items are reintegrated into the system via take-back schemes or secondary distribution networks, where they are subjected to systematic recognition, categorization, and condition evaluation. The outcomes of this assessment determine the subsequent allocation of garments to suitable value-retention or material recovery routes, including secondary commercialization, restorative processing, fiber-level reclamation, or controlled end-of-life handling. Persistent monitoring, combined with cross-stage data consolidation, enables system-wide visibility and facilitates the coordinated movement of materials within closed-loop textile networks [12].

AI functions as a central technological driver for the operationalization and expansion of circular fashion workflows. Advanced visual analysis and retrieval mechanisms powered by AI enable automated apparel recognition and organization, while learning-based models contribute to evaluating garment condition, inferring material composition, and anticipating demand patterns. In addition, AI facilitates evidence-based decision processes through the examination of lifecycle-level data, allowing the strategic refinement of reuse and material recovery pathways. By integrating automated operations, foresight-oriented analytical models, and intelligent retrieval mechanisms, AI improves process effectiveness, lowers systemic operational expenditure, and enables the practical deployment of circular fashion workflows within industrial textile contexts.

3.4.1 AI-driven textile recycling and material reuse

Rather than extracting new raw inputs, material reuse operates by sustaining the functional relevance of existing textile matter within successive value chains, thereby constraining waste accumulation and resource demand. At an operational level, textiles are maintained within functional circulation with little to no transformative intervention, preventing their premature exclusion from productive

systems. Illustrative practices include the transformation of residual fabric offcuts into functional accessories (e.g., carry items or home furnishings), the redistribution of preowned apparel through resale or donation channels, the reintegration of excess yarns or unused fabric stocks into subsequent design lines, and the conversion of industrial textile residues into applications such as thermal insulation or cushioning materials. Within circular textile systems, material reuse functions as a value-preservation strategy that reduces raw material extraction and downstream waste proliferation while simultaneously alleviating economic and ecological system loads.

Within textile recycling ecosystems, AI functions as a catalytic enabler by overcoming the sector's most persistent bottleneck: precise discrimination and systematic segregation of heterogeneous material compositions. Existing recycling workflows largely employ manual screening or elementary sensor technologies – approaches that fail to maintain operational efficiency or classification accuracy under conditions of material hybridity, garment variability, and industrial-scale waste throughput. Learning-enabled visual analytics systems facilitate automated decomposition of textile characteristics by processing imaging and sensor signals to derive compositional, structural, and quality-related descriptors without manual intervention. Fine-grained recognition of textile attributes underpins the rational structuring of postconsumer material flows, ensuring that each item enters a recovery loop aligned with its intrinsic properties, which, in turn, stabilizes process purity and amplifies overall system efficiency [1].

Beyond recognizing textile attributes, AI functions as a self-adaptive control mechanism that evaluates system-level data, determines optimal processing routes, and continuously restructures recycling operations to improve efficiency and material recovery. By interpreting accumulated operational records, cost metrics, and sustainability indicators, learning-based models autonomously infer the optimal end-of-life strategy for individual textile items, distinguishing whether they should undergo physical reprocessing, molecular-level recovery, or be reintegrated with minimal transformation. By learning from how recycling systems have behaved over time, computational models can anticipate when material volumes will surge, when equipment strain is likely to occur, and when energy demand will peak, enabling operations to adjust before disruptions arise rather than responding after losses occur. Consequently, recycling infrastructures guided by intelligent algorithms exhibit leaner operational behavior, extract greater value from recovered textiles, and exert a substantially lower ecological burden, reinforcing closed-loop production models within the textile sector [13].

Image-based retrieval mechanisms powered by intelligent models enable the discovery of previously utilized textile items by establishing visual correspondences across extensive digital repositories, thereby making repeated material utilization technically feasible. By analyzing visual characteristics such as form, surface structure, coloration, and motif, AI-powered retrieval systems match garments or textile samples with existing inventories, enabling the identification of items suitable for direct reuse or refurbishment. Consequently, reliance on virgin inputs is diminished, while surplus, returned, or postconsumer textiles can be reintegrated into production or consumption cycles with minimal alteration, maximizing material efficiency.

In circular textile operations, AI examines the visual and structural traits of garments to decide whether each item should continue in use or be directed toward material recovery, automating choices that were previously made by humans.

Integrating AI-based visual analysis with virtual replicas and inventory systems allows textile operations to forecast reuse opportunities, predict demand, and gauge ecological effects in advance, strengthening transparency and enabling more sustainable material flows.

3.4.2 Intelligent production cycle and waste reduction

In contemporary textile manufacturing, production cycles are governed by adaptive feedback loops, where information collected during one phase of fabrication or postprocessing dynamically guides decision-making in subsequent stages. In the production cycle, the garment image retrieval system functions as a live interpreter of visual data, continuously translating observed patterns into actionable decisions that guide subsequent manufacturing steps. By continuously interpreting garment imagery and identifying visually analogous items, the system produces actionable insights that inform inventory, production, and demand strategies, enabling manufacturers to adapt outputs based on recurring reuse patterns and material trends [14].

Inside the circular textile system, insights derived from visual retrieval continuously inform and adjust decisions at each stage of the material lifecycle. By interpreting patterns of similarity across textile items, manufacturers can recalibrate production processes, align stock levels with actual demand, and minimize redundant material output. Through iterative feedback loops derived from market and inventory intelligence, production processes are dynamically aligned with resource availability, establishing a responsive and efficiency-driven manufacturing cycle. Consequently, adaptive manufacturing workflows limit excessive output, maximize the use of available materials, and elevate the efficiency of overall operations [12].

In intelligent textile operations, the ability to reliably distinguish each garment plays a pivotal role in curbing unnecessary waste and enhancing process efficiency. When garments are inaccurately classified, materials that could reenter production or recycling loops are misdirected, undermining system efficiency and resource retention.

4. Industrial impact of the proposed M-AlexNet-based apparel image retrieval framework

The proposed apparel image retrieval framework functions as an enabling technology for smart and sustainable textile manufacturing systems. By integrating deep feature learning with optimized feature selection, the framework improves retrieval accuracy while reducing computational complexity. Through the extraction of informative visual representations, the system can analyze essential garment characteristics such as material structure, texture, color distribution, and design patterns. These capabilities enable reliable garment identification and similarity assessment, allowing automated decision support across multiple textile manufacturing processes.

From a sustainability perspective, the framework contributes to both material efficiency and computational optimization. Accurate visual recognition supports precise garment identification, sorting, and classification, improving the allocation

of textile resources while facilitating reuse and recycling processes. At the computational level, dimensionality reduction and redundancy elimination reduce processing requirements and energy consumption, enabling faster and more efficient decision-making. By improving both operational efficiency and resource utilization, the framework supports scalable and environmentally responsible textile manufacturing systems.

One of the primary applications of the framework is automated garment sorting and classification. By analyzing garment attributes such as texture, shape, color distribution, and stylistic characteristics, the system can accurately group visually similar items within large apparel datasets. Automated classification reduces reliance on manual sorting while improving operational speed and consistency across large-scale textile operations. Reliable similarity evaluation minimizes sorting errors and ensures that garments are directed to appropriate downstream processes such as reuse, resale, recycling, or material recovery. Consequently, the framework supports efficient garment handling within modern textile manufacturing and recycling environments.

The framework also supports textile pattern and design matching. By comparing visual characteristics such as motif geometry, repetition structure, spatial layout, and color distribution, the system can retrieve visually related textile patterns from large design archives. This capability assists designers in verifying originality, exploring design variations, and accelerating the development of new textile designs. Automated pattern retrieval is particularly valuable in environments involving traditional or ethnic textile motifs, where similar patterns may appear across different regions or time periods. From an industrial perspective, such functionality helps prevent unintentional design duplication and supports intellectual property protection while enhancing creative efficiency within digital textile design workflows.

Quality control and inspection represent another critical application area. Garment images captured during production can be compared with benchmark reference samples stored in a quality database, enabling objective similarity evaluation. This automated inspection mechanism allows manufacturers to detect visual defects related to fabric appearance, surface structure, or finishing quality. Continuous monitoring of production output enables early identification of defective garments, preventing faulty products from entering distribution channels and reducing material waste associated with defective manufacturing. As a result, intelligent visual inspection improves product reliability while strengthening overall quality assurance processes.

Maintaining color consistency across production batches is another challenge addressed by the framework. By enabling objective comparison between newly produced fabrics and reference samples, the system can identify subtle variations in color distribution and tonal characteristics that may indicate inconsistencies in dyeing processes. Automated color evaluation allows manufacturers to detect deviations early and implement corrective actions, such as process adjustments or redyeing. This capability improves product consistency while reducing reprocessing costs and material waste, contributing to more efficient and sustainable textile production.

Beyond quality control, the framework also contributes to resource optimization across digital and physical textile infrastructures. Feature optimization techniques reduce memory requirements and computational load, enabling real-time

deployment in large-scale industrial environments. Reduced processing demands lower energy consumption associated with digital operations, while improved garment identification supports more efficient material utilization throughout the textile lifecycle. Through these combined efficiencies, the framework enables more sustainable management of textile production systems.

The system further supports circular fashion initiatives by enabling reliable recognition of garments throughout multiple lifecycle stages. Accurate identification allows products returning from consumer use or recovery streams to be systematically analyzed and redirected toward appropriate reuse, resale, or recycling pathways. Garments suitable for continued use can be redirected to second-hand distribution channels, while items with limited reuse potential can be allocated to suitable recycling processes. This structured evaluation process extends product lifecycles and reduces environmental impacts associated with textile waste.

Within recycling environments, the retrieval system assists in identifying garments with similar materials, structures, or design characteristics, allowing textiles to be grouped for appropriate refurbishment or recycling processes. Improved identification of garments entering recycling streams increases the proportion of materials that can be effectively recovered and reused. By strengthening material recovery pathways, the framework supports the transition toward resource-efficient textile systems that minimize reliance on virgin raw materials.

Accurate retrieval and classification also contribute to waste reduction within textile production cycles. Improved garment identification minimizes classification errors and prevents the unnecessary rejection of usable textiles. By ensuring that a greater proportion of garments are directed toward productive reuse or recycling pathways, the framework improves the efficiency of circular production loops. Through the integration of automated decision support and efficient digital processing, the system contributes to more sustainable and intelligent textile manufacturing systems.

Overall, the proposed retrieval framework enhances multiple textile industry operations by transforming traditionally manual and error-prone processes into automated, data-driven workflows. These capabilities improve operational efficiency, strengthen quality management, support sustainable resource utilization, and enable circular textile production models. By integrating intelligent garment recognition into manufacturing, design, quality control, and recycling processes, the framework provides a practical technological foundation for advancing smart and sustainable textile manufacturing ecosystems.

Table 1 summarizes how image retrieval, particularly the proposed M-AlexNet-based framework, enhances diverse textile industry applications by transforming manual, error-prone processes into automated, accurate, and sustainability-oriented operations with measurable industrial benefits.

5. Challenges and future directions

Even though the AI-driven garment retrieval system performs effectively, certain technical and operational issues remain unresolved, requiring deeper investigation to enhance its reliability and adaptability. The development of reliable AI garment retrieval is constrained by insufficient access to large, varied datasets with precise annotations, which restricts model performance and adaptability. Many available

Application area	Baseline process	Retrieval role	M-AlexNet impact	Industrial outcome
Automated sorting	Manual, error-prone	Similarity-based grouping	Automated, high precision	Reduced labor, higher accuracy
Pattern and design matching	Manual comparison	Visual pattern retrieval	Feature optimization	Faster design cycles
Quality control and inspection	Human-dependent inspection	Reference-based visual comparison	Reliable defect detection	Standardized quality
Fabric defect detection	Late-stage fault discovery	Retrieval of known defect patterns	Early and reliable defect identification	Reduced rework and energy use
Color consistency control	Trial-and-error color adjustment	Color distribution comparison	Stable and repeatable color evaluation	Lower rejection and redyeing rates
Apparel recommendation	Rule-based or text-driven suggestions	Visual similarity-based matching	Data-driven personalized retrieval	Enhanced customer satisfaction
Textile recycling	Manual separation of materials	Identification of reusable vs. recyclable items	Accurate material-level classification	Higher recovery and lower contamination
Material reuse	Limited reuse due to poor identification.	Detection of reusable garments	Increased reuse precision	Reduced raw material consumption
Circular fashion workflows	Fragmented, linear processing	Lifecycle-aware garment routing	Closed-loop, adaptive decision-making	Improved circularity and sustainability

Table 1.
Integrated impact of image retrieval in textile industry applications.

datasets fall short in representing the complexities of actual textile environments, including variations in material types, traditional design motifs, aging effects, and deformations occurring after consumer handling. These constraints can undermine the ability of M-AlexNet to learn feature representations that remain robust across unseen scenarios, especially when garment images are captured in uncontrolled or inconsistent visual environments.

The same garment can appear visually inconsistent because image capture is influenced by random factors such as how apparel bends, how light falls on it, how much of it is visible, and where the camera happens to be positioned. Even with the representational advantages introduced by Mish activation, visually complex garments – such as multilayered outfits, heavily ornamented textiles, or pieces composed of multiple materials – pose persistent difficulties for models that rely solely on image-based analysis. Collectively, these constraints suggest that effective retrieval solutions must balance resilience to complex, real-world garment characteristics with strict efficiency and accuracy requirements.

Beyond algorithmic performance, practical adoption is constrained by scalability concerns, as even with JSE-PCC compressing the feature space, executing retrieval models on limited-capacity hardware typical of production and recycling environments remains a nontrivial obstacle. For many textile producers, especially those operating with manual workflows and aging machinery, the move toward

intelligent systems is slowed not by technical resistance but by the financial constraints associated with large-scale infrastructure modernization.

The framework also opens multiple opportunities for further investigation aimed at refining its capabilities and expanding its use across more complex textile scenarios. Future extensions could investigate transformer-based vision architectures to better model global visual relationships within intricate textile designs, thereby complementing the localized feature learning of convolutional networks, while alternative learning paradigms, such as self-supervised and contrastive strategies, may leverage vast unlabeled image collections to reduce dependence on labor-intensive annotation processes.

An additional avenue involves expanding the retrieval framework beyond images alone by incorporating complementary information sources, such as descriptive text, identification tags, and sensor-generated data. When image data is interpreted alongside identifiers and contextual signals, the framework gains both sharper matching capability and a clearer longitudinal view of each garment's journey. Designing compact learning models that can operate at the edge would allow garment analysis and sorting to occur immediately within production facilities, lowering response delays, cutting power usage, and reducing reliance on remote computing resources.

Making the system's decisions transparent and interpretable would play a key role in convincing industry practitioners to rely on AI-driven solutions. Explaining why specific garments are matched, rather than only presenting the match itself, enables clearer oversight, strengthens user confidence, and supports alignment with regulatory and sustainability requirements. Collectively, these lines of exploration indicate that the framework can evolve into a practical, transparent, and resource-conscious system capable of supporting intelligent textile operations at scale.

6. Conclusion

Rather than presenting an isolated technical solution, this chapter introduces an intelligent garment retrieval and feature refinement framework designed to confront key sustainability-related bottlenecks within textile production systems. By coupling enhanced deep feature extraction with selective feature pruning driven by information content and correlation, the framework balances strong retrieval performance against reduced processing overhead. This balance of accuracy and efficiency enables the system to operate effectively within expansive textile operations, where automated decision-making and consistent reliability are non-negotiable.

Functioning as an embedded decision layer, the framework provides intelligent visual insight across diverse operational functions – ranging from online sorting and inspection to material recovery, stock coordination, and manufacturing strategy alignment. By leveraging refined visual descriptors and precise similarity reasoning, the framework allows automated systems to recognize, group, and associate garments with little reliance on manual input. By shifting critical judgments from human operators to data-driven automation, this capability strengthens adaptive manufacturing operations, minimizes reliance on manual checks, and enables feedback-driven production cycles.

In environmental terms, the framework advances circular production practices by enabling more precise garment recognition, thereby reducing the likelihood of incorrect sorting and unnecessary material loss.

Reliable garment matching allows items with remaining value to be directed toward appropriate circulation channels, preventing premature discard and enabling extended use through secondary markets or material reprocessing. Simultaneously, compressing the feature space via JSE-PCC decreases processing effort, power usage, and system demands, thereby linking algorithmic efficiency with broader environmental sustainability objectives.

The work presented in this chapter establishes automated garment image analysis as an essential enabler for future textile systems that prioritize intelligence, efficiency, and environmental responsibility. The framework connects advanced computational learning with efficiency-driven design and on-site usability, helping textile operations move toward more digitally integrated modes of production. As textile production increasingly integrates digital computation, automated operations, and sustainability-oriented decision logic, intelligent AI-driven frameworks like the one introduced here are likely to become central in defining how future textile ecosystems operate and self-regulate.

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Conflict of Interest

The authors declare no conflict of interest.

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