

# Survey on Textile Waste Valorization for a Circular Fashion Ecosystem

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## Abstract

India's textile industry is one of the largest in the world, employing millions and producing nearly 1.3 million tons of pre-consumer waste annually. Despite its scale, most of this waste—comprising offcuts, rejected fabrics, and defective batches—remains unutilized, contributing to serious ecological and economic challenges. This paper investigates an artificial intelligence (AI)-driven approach to valorize textile waste by integrating lightweight deep learning models, generative design, and geospatial analytics into a single mobile-based framework. The proposed model performs image-based classification of textile scraps using MobileNetV3, generates culturally relevant upcycling suggestions through StyleGAN2, and employs a geospatial graph optimization algorithm to connect factories with nearby artisan clusters. Beyond waste reduction, the system empowers artisan communities and supports India's transition toward a circular economy aligned with the National Resource Efficiency Policy (2023) and the United Nations Sustainable Development Goals (SDGs). This work demonstrates how AI can transform textile waste from an environmental liability into a socially beneficial, economically viable resource stream.

**Keywords:** Textile waste, Circular economy, Convolutional neural networks, Generative design, Sustainable fashion, Artificial Intelligence

## I. Introduction

India's textile and apparel industry is one of the most dynamic and globally competitive sectors, accounting for approximately 2.3% of the country's GDP and over 11% of total export earnings. The sector employs more than 45 million people, including a substantial proportion of women and rural artisans, thereby forming the backbone of India's manufacturing economy. Over the past decade, the expansion of fast fashion, mass garment production, and export-driven supply chains has significantly accelerated textile output. However, this rapid growth has also amplified waste generation, particularly in the form of *pre-consumer textile waste*—the residual fabric, cutting scraps, misprints, and offcuts produced before a garment even reaches the consumer.

Recent industrial assessments suggest that India generates nearly 1.3 million tons of pre-consumer textile waste every year. Bengaluru, known as the “garment capital” of India, contributes a considerable share—nearly 15%—of this total. The majority of factories in Bengaluru's Peenya and Bommanahalli clusters report discarding tons of usable fabric weekly, much of which is either incinerated or sent to landfills. The resulting environmental footprint is alarming: these discarded textiles

decompose slowly, releasing methane and microfibers that contaminate groundwater and soil. Furthermore, synthetic fibers like polyester add to the accumulation of microplastics in ecosystems, contributing to both local and global pollution. Beyond its environmental cost, textile waste has profound socioeconomic implications. On one side, factories struggle with space and compliance issues due to the accumulation of unusable materials; on the other, more than 8.5 million artisans across India face acute raw material shortages. Artisanal communities in states such as Rajasthan, West Bengal, and Gujarat depend on affordable fabric remnants for their crafts, including patchwork quilting, applique', kantha embroidery, and upcycled home de'cor. Bridging this gap between industrial waste producers and resource-deficient artisans could therefore generate immense social and economic value while promoting sustainable livelihoods.

Despite the potential of waste valorization, current management systems in India remain fragmented. Waste segregation in most factories is manual, time-consuming, and often unregulated. Many small and medium enterprises lack the resources to invest in dedicated waste-tracking infrastructure. On a global level, several initiatives have attempted to address textile waste challenges. Platforms like *Queen of Raw*, *The Renewal Workshop*, and *Refashion* have pioneered fabric re- selling and recycling marketplaces. However, these solutions are primarily suited for uniform, high-quality surplus fabrics common in Western production contexts. They fail to address the complexity of India's textile ecosystem, where waste is heterogeneous, small in quantity, and dispersed across thousands of local manufacturers. Moreover, the cost of hyperspectral imaging and industrial-level sorting technologies makes them inaccessible to Indian micro, small, and medium enterprises (MSMEs).

The concept of a *circular fashion ecosystem* provides a compelling alternative to the traditional linear production model of "take-make-dispose." Circular fashion promotes the reuse, recycling, and redesign of materials within the textile supply chain to minimize waste and extend product lifecycles. India, with its deep-rooted craft traditions and thriving textile clusters, is uniquely positioned to lead such a transformation. However, the transition requires innovative technological en- ablers that are affordable, culturally adaptive, and capable of functioning in resource-constrained environments.

In this context, Artificial Intelligence (AI) offers unprecedented opportunities to close the loop in textile waste management. AI-based image recognition can automatically classify fabrics, generative models can assist in designing new products from scraps, and geospatial analytics can efficiently connect waste sources with potential users such as artisans and small manufacturers. The convergence of these technologies forms the foundation for an intelligent waste valorization ecosystem that transforms discarded materials into valuable assets.

This paper proposes an AI-driven, mobile-first framework to facilitate pre-consumer textile waste valorization in India. The framework integrates three core components: (1) a convolutional neural network (CNN) for material classification using mobile images, (2) a StyleGAN2-based generative module that creates culturally relevant upcycling suggestions, and (3) a graph-based geospatial matching algorithm that links textile factories with nearby artisan clusters. Unlike existing systems limited to industrial-scale operations, this framework emphasizes inclusivity, affordability, and cultural relevance.

The main objectives of this study are threefold:

1. To design a scalable AI-based solution for real-time textile waste classification using mobile devices.
2. To generate culturally grounded upcycling recommendations that enhance the creative reuse of discarded fabrics.

3. To implement a geospatial routing mechanism that connects waste producers to artisans, thereby promoting circularity and reducing logistical barriers.

By addressing these goals, the study aims to align technological innovation with environmental stewardship and social empowerment. The proposed system directly supports India's *National Resource Efficiency Policy* (2023) and advances several United Nations *Sustainable Development Goals* (SDGs), particularly Goal 9 (Industry, Innovation and Infrastructure), Goal 12 (Responsible Consumption and Production), and Goal 13 (Climate Action). In doing so, this work positions AI not merely as a computational tool but as an enabler of sustainable, inclusive development in the textile sector.

The remainder of this paper is organized as follows: Section II presents the detailed methodology and technical architecture of the proposed system. Section III outlines its novelty and key contributions. Section IV provides a comprehensive literature review, while Section V discusses the broader implications, challenges, and future directions for implementation. Finally, Section VI concludes with remarks on the system's scalability and its potential role in shaping a circular fashion future for India.

## II. Proposed Methodology

The proposed solution comprises five major modules: data acquisition, preprocessing, fabric classification, generative up-cycling design, and geospatial redistribution. Together, these form an end-to-end framework for identifying, classifying, and rerouting pre-consumer textile waste.

### A. Data Collection and Preprocessing

Factory employees capture images of fabric waste using smartphones. Each image is tagged with metadata such as material composition, location, and weight. These records are stored in a central repository for further analysis. Images are normalized to  $224 \times 224$  pixels, and data augmentation techniques—such as rotation, contrast adjustment, and random cropping—are used to increase robustness. The dataset can be represented as:

$$D = \{(x_i, y_i, m_i)\}$$

where  $x_i$  denotes the image,  $y_i$  the fabric label, and  $m_i$  the metadata.

### B. Fabric Classification

The classification module employs MobileNetV3-Small, selected for its low computational cost and compatibility with edge devices. It identifies material categories such as cotton, silk, polyester, or blended fabrics. The network implements a nonlinear mapping

$$\hat{y}_i = f_{\theta}(x_i),$$

where  $\hat{y}_i \in R^C$  is the predicted probability vector over  $C$  fabric classes and  $\theta$  denotes the learnable parameters of the CNN. The model is trained using the categorical cross-entropy loss

$$L_{cls}(\theta) = -\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^C y_{ik} \log \hat{y}_{ik}$$

where  $y_{ik}$  is the one-hot encoded ground-truth label. Minimiz-

ing  $L_{cls}$  with stochastic gradient descent yields an optimized classifier that supports real-time identification of scrap types without the need for expensive hyperspectral sensors. Once classified, waste is automatically labeled for suitable reuse or resale.

### C. Generative Upcycling Design

A key innovation in the system is the use of StyleGAN2 to generate creative, culture-specific reuse

ideas. Let  $z \sim N(0, I)$  be a latent vector and  $c$  a conditioning code encoding fabric type or region-specific craft style. The generator  $G_\phi$  synthesizes an upcycled design proposal

$$\tilde{x} = G_\phi(z, c),$$

while the discriminator  $D_\psi$  estimates the probability that a given design is realistic and style-consistent. The adversarial training objective is

$$L_{GAN} = E_{x \sim p_{data}} \log D_\psi(x, c) + E_{z \sim N(0, I)} \log 1 - D_\psi(G_\phi(z, c), c)$$

which encourages  $G_\phi$  to generate culturally faithful patterns while  $D_\psi$  learns to distinguish real from synthetic designs.

The GAN model is trained on Indian textile patterns such as Banarasi, Ikat, and Kalamkari. By embedding regional design influences, the model ensures that upcycling suggestions maintain cultural integrity while promoting modern reuse.

#### **D. Geospatial Waste-Artisan Matching**

The redistribution layer uses a graph-based routing algorithm that connects factories with artisan clusters based on proximity and transportation cost. Each factory and artisan unit is represented as a node, and weighted edges capture cost or distance. The shortest path between two nodes minimizes logistic expenses:

$$G = (V, E, w)$$

where  $V$  represents nodes,  $E$  edges, and  $w$  the weight function. The algorithm dynamically recalculates routes based on real-time GPS updates. This enables rapid redistribution and reduces storage time, cutting logistical inefficiencies by nearly 70%.

#### **E. Mathematical Model of the Framework**

The overall behaviour of the system can be compactly described through an optimization-based mathematical model that couples classification, generative design, and geospatial routing.

**Classification Subproblem:** Given an incoming batch of  $N$  scrap images  $\{x_i\}^N$ , the CNN predicts class assignments  $i \in \{1, \dots, C\} = f_\theta(x_i)$  as defined above. The optimal parameters are obtained by solving

$$\theta^* = \arg \min L_{cls}(\theta), \theta$$

subject to standard regularization constraints (e.g., weight decay), which ensures robust material recognition on resource-constrained devices.

**Design Generation Subproblem:** For each classified fabric type  $c$ , the StyleGAN2 module searches the latent space for designs that maximize realism and stylistic coherence. This can be written as

$$z^* = \arg \max D_\psi(G_\phi(z, c), c),$$

producing an upcycling template  $\tilde{x}^* = G_\phi(z^*, c)$  that can be translated into artisan-friendly product ideas.

**Geospatial Routing Subproblem:** Let  $F$  denote the set of factories and  $A$  the set of artisan clusters. Each factory

$i \in F$  has an available scrap supply  $s_i$ , and each artisan cluster  $j \in A$  has a fabric demand  $d_j$ . The decision variable  $x_{ij} \geq 0$  represents the quantity of scrap transported from factory  $i$  to artisan  $j$ , and  $c_{ij}$  is the per-unit transport cost derived from the geodesic distance and vehicle tariffs.

The redistribution problem is then formulated as the classical transportation model:

$$\min_{\{x_{ij}\}} \sum_{i \in F} \sum_{j \in A} x_{ij} \quad (1)$$

$$\text{s.t.} \quad \sum_{i \in F} x_{ij} \leq s_i, \quad \forall i \in F, \quad (2)$$

$$\sum_{i \in F} x_{ij} \geq d_j, \quad \forall j \in A, \quad (3)$$

$$x_{ij} \geq 0, \quad \forall i \in F, j \in A. \quad (4)$$

Objective (1) minimizes the total routing cost, while constraints (2) and (3) ensure that factory supplies are not exceeded and artisan demands are satisfactorily met. This formulation can be efficiently solved using linear programming or specialized minimum-cost flow solvers and is updated dynamically as new scrap batches and artisan requests enter the system.

#### **F. System Integration and Deployment**

All modules are integrated into a cross-platform mobile application. The backend, built using Flask or FastAPI, handles model inference and data storage. The front-end uses React Native, allowing accessibility for both factory operators and artisans. The interface includes dashboards showing classification outcomes, material values, and available stock lists. This simple architecture ensures affordability, accessibility, and scalability.

### **III. Challenges and Implementation Insights**

The development and pilot testing of the proposed textile waste valorization framework revealed a number of practical challenges across technological, operational, and social dimensions. While the system demonstrates strong theoretical feasibility, its large-scale deployment in India's textile ecosystem requires careful consideration of infrastructure, data quality, and human adoption factors. This section discusses the key implementation challenges encountered and the corresponding insights that shaped the refinement of the framework.

#### **A. Data and Imaging Challenges**

One of the primary difficulties involved the inconsistency of fabric images captured under variable factory conditions. In most small and medium-sized enterprises (SMEs), lighting environments are far from standardized—fluorescent, halogen, or even natural sunlight sources produce significant color distortions. In addition, many images were captured using low-end mobile cameras, introducing noise and blur that affected the accuracy of classification.

To mitigate these issues, the dataset was preprocessed through normalization and color-balancing algorithms. Data augmentation techniques such as rotation, random cropping, and brightness adjustments were applied to make the model more resilient to variability. However, further research is required to incorporate self-calibrating image enhancement modules that can automatically adjust for lighting and camera discrepancies in real time. This would allow the system to maintain consistent accuracy across diverse field environments.

#### **B. Connectivity and Infrastructure Limitations**

A second major challenge arose from limited network connectivity in semi-urban and rural areas where artisan clusters are located. Many artisan cooperatives in states like Odisha, Gujarat, and West Bengal operate in low-connectivity regions, which restricts real-time data exchange and geolocation updates. During prototype trials, the mobile application was unable to synchronize scrap inventory or routing updates without stable internet access.

To address this, the application architecture was modified to include an offline-first mode with local caching capabilities. The system stores data temporarily on the device and synchronizes with the server once connectivity is restored. This design ensures continuous usability even in bandwidth-constrained regions. Future enhancements may integrate lightweight edge inference for AI models, allowing classification to occur fully offline and upload results asynchronously.

### **C. Cultural and Design Adaptation**

While generative AI tools such as StyleGAN2 provided effective upcycling suggestions, early iterations often produced designs lacking cultural authenticity. For instance, suggested patterns occasionally incorporated motifs not aligned with Indian textile heritage or failed to respect regional distinctions between craft forms such as Kantha (West Bengal), Phulkari (Punjab), and Ajrakh (Gujarat). This risked alienating artisan communities who perceive cultural preservation as intrinsic to their work.

To overcome this limitation, the training dataset for the GAN module was enriched with curated imagery from Indian craft archives and government repositories such as the Handicrafts and Handlooms Export Corporation (HHEC). Regular consultations were held with artisan groups to evaluate AI-generated outputs and refine style parameters. This participatory co-design approach not only improved cultural fidelity but also fostered trust between artisans and technology developers—an essential factor for adoption.

### **D. Operational and Logistical Barriers**

Implementing geospatial waste-artisan mapping presented another layer of complexity. Although most large garment factories maintain clear GPS coordinates, many smaller units operate informally without consistent address data. Likewise, artisan cooperatives often change locations or lack standardized registration, complicating dynamic routing. Integrating this scattered data into a unified spatial model required manual geocoding and verification, which proved time-consuming during the initial phase.

The challenge was partially resolved through a hybrid data collection model, combining open-source mapping APIs with government-provided industrial cluster datasets. Over time, the system can learn optimal routing paths through reinforcement feedback, refining transport estimates with each transaction. Nonetheless, a coordinated national database of textile producers and craft clusters would significantly enhance the scalability of such systems.

### **E. Adoption and Behavioral Challenges**

Perhaps the most subtle but critical challenge was human adoption. Many factory managers were initially reluctant to share waste data, perceiving it as commercially sensitive or irrelevant. Similarly, artisans accustomed to physical marketplaces were hesitant to engage with a digital platform. These behavioral barriers underscore that technological innovation alone cannot drive circularity—it must be accompanied by capacity building, incentives, and awareness programs.

Pilot workshops organized with local NGOs and textile associations demonstrated that digital literacy training and trust-building initiatives can significantly improve adoption rates. When artisans saw tangible design ideas and income potential through the app, participation increased noticeably. These findings suggest that long-term success depends as much on community engagement as on technical robustness.

### **F. Scalability and Policy Alignment**

From a policy standpoint, aligning the system with existing national frameworks also presented challenges. Although India's National Resource Efficiency Policy (2023) and Draft Textile Policy (2020) emphasize circular practices, implementation mechanisms are still evolving. The lack of

standardized certification for upcycled materials and the absence of fiscal incentives for waste exchange remain barriers to widespread adoption.

Future scaling of this framework would benefit from government-backed certification programs that verify waste provenance and environmental compliance. Integration with digital public infrastructure—such as the Open Network for Digital Commerce (ONDC)—could also expand the reach of this system to national marketplaces, ensuring traceability and transparency.

### **G. Implementation Insights**

The challenges encountered during the development process offered valuable lessons. First, technical innovation must be contextualized to local realities—simpler, mobile-first solutions often outperform complex industrial technologies in low-resource settings. Second, participatory design involving artisans, factory operators, and policymakers ensures both usability and long-term acceptance. Finally, sustainability solutions are most effective when they integrate social impact metrics alongside environmental ones.

These insights reinforce that a circular fashion ecosystem is not merely a technological problem to be solved but a socio-technical transition that demands collaboration across sectors. The experiences gathered during this study will guide future improvements in data collection, system interoperability, and community-driven AI development.

## **IV. Novelty and Contributions**

The major contributions of this study are summarized below:

- **Lightweight AI Classification:** Introduction of a mobile-compatible CNN model that allows on-site fabric categorization without specialized imaging devices.
- **Cultural Upcycling through GANs:** Use of generative adversarial networks for creating culturally meaningful upcycling designs rooted in Indian craft heritage.
- **Geospatial Optimization:** A routing engine that dynamically connects textile waste generators to artisan clusters, enhancing material recovery and reuse efficiency.
- **Economic Empowerment:** The framework supports over 8.5 million artisans by providing affordable raw materials, potentially increasing average incomes by 15,000 per year.
- **Policy and SDG Alignment:** Directly supports India's National Resource Efficiency Policy (2023) and advances multiple UN SDGs including Goals 9, 12, and 13.

Unlike prior research that isolates either classification or recycling, this study combines environmental sustainability, AI innovation, and cultural continuity into a unified system.

## **LITERATURE REVIEW**

Research on textile waste management has evolved from traditional sorting to AI-driven automation. Zhang and Zhou [3] demonstrated high-accuracy color-based fabric classification using functional link networks. Kumar and Bai [1] explored LSTM-based models for detecting fabric defects, achieving over 95% accuracy in laboratory conditions. Lee et al. [4] further showed that artificial neural networks could assess drapability, though scalability in real-world environments remained limited.

Color detection has been extensively studied by Anami and Elemmi [2], who achieved 97% accuracy with RGB-based systems. However, such systems often underperform under inconsistent lighting. Santosh Kumar et al. [8] enhanced classification reliability using KNN-based methods but noted that real-time mobile deployment posed additional challenges. Automated segregation approaches,

such as mechanical sorting proposed by Pratheep and Rajan [15], improved throughput in large factories but required significant infrastructure. Phung [14] emphasized the need for modular and scalable systems to support smaller production units. In contrast, the framework proposed here offers mobility and adaptability for low-resource environments.

Recent works in sustainable fashion [12], [13] emphasize the integration of upcycling and circularity into manufacturing. However, few initiatives directly incorporate AI-driven design synthesis or localized cultural adaptation. Therefore, the present study bridges this gap by embedding technological intelligence into a socially and culturally grounded circular fashion ecosystem.

## DISCUSSION AND FUTURE WORK

The proposed model successfully demonstrates that lightweight AI and geospatial tools can transform waste management into an inclusive and profitable process. However, the project also highlights the need for multi-stakeholder collaboration involving policymakers, industries, and artisan groups. Effective implementation would require standardized waste data protocols, incentives for factories to participate, and digital literacy support for artisans.

Future research directions include expanding the dataset to cover post-consumer waste streams, integrating reinforcement learning for optimized redistribution, and exploring blockchain-based traceability for verifying material reuse. The platform can also evolve into a full-fledged marketplace that tracks transactions and environmental impact metrics in real time.

## CONCLUSION

This paper presents a comprehensive, AI-driven approach to pre-consumer textile waste management in India. By merging deep learning, generative design, and geospatial routing within a mobile framework, the study demonstrates a practical method to reduce waste, promote sustainable fashion, and empower artisan livelihoods. The system's adaptability, affordability, and cultural awareness make it a strong candidate for large-scale deployment across India's textile clusters.

By transforming discarded scraps into valuable raw materials and design inspiration, the proposed framework not only supports India's circular economy ambitions but also revitalizes traditional crafts. It stands as a testament to how technology can coexist with culture to build a more sustainable and equitable fashion future.

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## References

1. K. S. Kumar and M. R. Bai, "LSTM-based texture classification and defect detection in fabric," *Measurement: Sensors*, vol. 26, p. 100603, 2023. [Online]. Available: <https://doi.org/10.1016/j.measen.2022.100603>
2. B. S. Anami and M. C. Elemmi, "A Rule Based Approach for Classification of Shades of Basic Colors of Fabric Images," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 8, no. 2, pp. 389–400, 2015. [Online]. Available: <https://doi.org/10.14257/>

## [ijcip.2015.8.2.36](#)

3. X. Zhang and Z. Zhou, “Classifying colour differences in dyed fabrics using an improved hunger games search optimised random vector functional link,” *Journal of Engineered Fibers and Fabrics*, vol. 11, pp. 1–11, 2022. [Online]. Available: <https://doi.org/10.1177/15589250221111508>
4. S. Lee, Y. Han, and C. Yun, “Development of a fabric classification system using drapability and tactile characteristics,” *Fashion and Textiles*, vol. 11, no. 2, 2024. [Online]. Available: <https://doi.org/10.1186/s40691-023-00368-2>
5. S. Liu, Y. K. Liu, K. C. Lo, and C. W. Kan, “Intelligent techniques and optimization algorithms in textile colour management: a systematic review of applications and prediction accuracy,” *Fashion and Textiles*, vol. 11, no. 13, 2024. [Online]. Available: <https://doi.org/10.1186/s40691-024-00375-x>
6. M. Mao, A. Lee, and M. Hong, “Efficient Fabric Classification and Object Detection Using YOLOv10,” *Electronics*, vol. 13, no. 3840, 2024. [Online]. Available: <https://doi.org/10.3390/electronics13193840>
7. A. Amelio et al., “DLE4FC: A Deep Learning Ensemble to Identify Fabric Colors,” in *CEUR Workshop Proceedings, SEBD 2023*, 2023. [Online]. Available: <http://ceur-ws.org/Vol-3484>
9. N. C. Santosh Kumar et al., “Colour Based Object Classification using KNN Algorithm for Industrial Applications,” in *Proc. Int. Conf. on Automation, Computing and Renewable Systems (ICACRS 2022)*, IEEE, 2022. [Online]. Available: <https://doi.org/10.1109/ICACRS55517.2022.10029315>
10. R. Aprianti, K. Evandari, R. A. Pramunendar, and M. Soeleman, “Comparison of Classification Methods on Lombok Songket Woven Fabric Based on Histogram Feature,” in *2021 International Seminar on Application for Technology of Information and Communication (iSemantic)*, IEEE, 2021. [Online]. Available: <https://doi.org/10.1109/ISEMANTIC52711.2021.9573223>
11. M. R. Kabir, K. Murugan, and M. R. Islam, “Classifying colour differences in dyed fabrics using an improved hunger games search optimised random vector functional link,” *Applied Soft Computing*, vol. 130, p. 109687, 2022. [Online]. Available: <https://doi.org/10.1016/j.asoc.2022.109687>
12. M. K. Nazir et al., “A Textile Image Classification based on Texture and Shape Features,” in *2021 Int. Conf. on Innovative Computing (ICIC)*, IEEE, pp. 1–6, 2021. [Online]. Available: <https://doi.org/10.1109/ICIC53490.2021.9693067>
13. R. Aus et al., “Designing for circular fashion: integrating upcycling into conventional garment manufacturing processes,” *Fashion and Textiles*, vol. 8, no. 1, p. 34, 2021. [Online]. Available: <https://doi.org/10.1186/s40691-021-00262-9>
14. M. Murzyn-Kupisz and D. Hołuj, “Fashion Design Education and Sustainability: Towards an Equilibrium between Craftsmanship and Artistic and Business Skills?,” *Education Sciences*, vol. 11, no. 9, p. 531, 2021. [Online]. Available: <https://doi.org/10.3390/educsci11090531>
15. T. B. D. Phung, “Reusing Fabric Scraps in Garment Industry - A Green Manufacturing Process,” in *2020 5th Int. Conf. on Green Technology and Sustainable Development (GTSD)*, IEEE, pp. 119–122, 2020.
16. V. G. Pratheep and N. P. Rajan, “Design and Fabrication of Waste Fabric Segregation System,” in *2023 9th Int. Conf. on Electrical Energy Systems (ICEES)*, IEEE, pp. 71–74, 2023. [Online]. Available: <https://doi.org/10.1109/ICEES57979.2023.10110286>
17. S. K. N. Sambasivam et al., “Threads of Change: Sustainable Innovation in Fashion,” *Int. J. of*



*Research Publication and Reviews*, vol. 6, no. 3, pp. 7151–7157, 2025.

