

# XCotton: Advancing AI-Enabled Hardware/Software Integrated System for Foreign Fiber Cleaning

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## Abstract

Cotton is a critical agricultural product and industrial raw material, playing a key role in the national economies and people's living conditions, particularly in developing countries. However, cotton picking and processing often result in the contamination with various foreign fibers, such as hair, hemp rope, plastic film, and polypropylene rope. These contaminants are difficult to remove during textile processing and tend to break into small fragments, significantly reducing the quality of cotton products and negatively impacting the cotton industry. In this paper, we present an AI-enabled hardware-software integrated system—XCotton, for identifying and removing foreign fibers. Our system has been deployed in actual cotton production environments in the multiple regions in China, Central Asia, and Africa. XCotton achieves a cleaning efficiency of 1000kg/h, representing a 43% improvement, with only 14 kWh energy consumption (63% less). Moreover, XCotton brings significant business values to its manufacturer and clients. XCotton not only enhances the quality of cotton products but also contributes to the value-adding and upgrading of the cotton industry in developing regions, supporting economic growth and improving living conditions.

## Introduction

Cotton fabric manufacturing is often the first step towards industrialization of developing countries (Riello 2015; Jensen and Whitfield 2022). For many of the least development countries (LDCs), such as Afghanistan, Benin, Burkina Faso, Chad, Mali, and Tajikistan, cotton fabric manufacturing is one of the largest single sources of their exportation, bringing precious foreign-currency and employing many local citizens<sup>1</sup>. The growing cotton industry has profound social and economic impacts in those countries' modernization (Chapman 1990; Koh 2016).

However, those LDCs are often locked in the lower spectrum of the entire value chain of the global cotton industry (Poulton et al. 2004), partially due to the cotton planting, harvest, and cleaning are labor-intensive (Blaise and Kranthi 2019). Their cotton exportation is often primary cotton

goods (Chapagain et al. 2006). While recent progress in cotton planting and harvest mechanization has been reducing the labor consumption in those process, the burden of cotton cleaning drastically increases because the automated planting and harvest introduces many different types of contaminants into the cotton. These contaminants have to be manually cleaned to produce high quality (and high value) cotton products (Van der Sluijs and Hunter 2017). Thus, developing automated cotton cleaning methods is an imperative for the upgrading of cotton industry in those LDCs.

The advent of computer vision techniques such as (Zhang et al. 2021; Zhao et al. 2014) provide possibilities for recognizing various contaminants in the cotton in an automated fashion. With proper mechanic design, a large proportion of foreign materials could be removed with minimal involvement of human labors (Ramesh, Gnanamangai, and Mohanraj 2021). We reports on an exploration in this direction. We formed continuous collaboration with *ZhongMian Cotton Machinery*, a major manufacturer and supplier of cotton cleaning machines to a number of domestic and international cotton fabric producers. Our collaboration results in *XCotton*, which is featuring advanced AI-enabled hardware/software foreign fiber cleaning system.

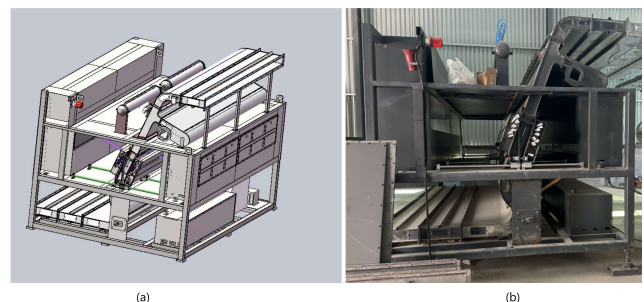


Figure 1: The contaminants cleaning machine: a) the CAD diagram and b) the prototype of the machine.

The approach has been deployed in ZhongMian's newest generation of lint cleaning machine— (Figure 1). The machine achieves a cleaning efficiency of 1000kg/h, representing a 43% improvement, with only 14 kWh energy consumption (63% less). The machines has been widely acclaimed by its clients around the world. Compared with

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<sup>1</sup><https://unctad.org/news/unlocking-hidden-value-cotton-products-african-least-developed-countries>

the last generation of lint cleaning machine, the profit from single machine increases 23%. By the 08/15/2024, ZhongMian had received 100+ orders of the new lint cleaning machine. ZhongMian estimated the annual revenue from the new lint cleaning machine would be 25.2M CNY ( $\approx$  3.5M USD). Among the confirmed orders, over 40% are from African and Central Asia clients. Ultimately, our approach would contribute to the upgrading of those countries' cotton industry, thus enabling positive social and economic impacts through improvements in the global cotton value chain. Specifically, our work's contribution are tri-fold:

- *Approach.* We designed an AI-enabled hardware/software integrated system for foreign fiber detection. The system features a line-scan camera, laser light source, and variable-speed conveyor, with a core real-time recognition algorithm based on image texture structure. This innovative approach effectively detects foreign fibers and offers scalability for broader industrial applications.
- *Evaluation.* We collected over 3,000 images containing foreign fibre to conduct experiments. This extensive dataset allowed us to thoroughly evaluate the system's real-time recognition capabilities and validate its practical effectiveness in industrial settings. We conducted extensive evaluations to the XCotton approach in experimental and production environments, demonstrating its effectiveness in minimizing human effort in lint cleaning.
- *Deployment.* XCotton has been successfully deployed in ZhongMian's newest generation of lint cleaning machines. This deployment demonstrated significant technical and commercial benefits, as well as potential of upgrading cotton industry in LDCs.

## Background–Cotton Cleaning

Foreign fiber contamination in cotton poses significant challenges in maintaining the quality of cotton products. Foreign fibres (see Figure 2) primarily include: (a)synthetic fiber, (b)fluorescent white polypropylene, (c)non-fluorescent white polypropylene, (d)hair, (e)white mulch film, (f)colored mulch film, (g)colored burlap bag piece, (h)colored polypropylene. Many methods have been developed to address this issue, which can be categorized into traditional approaches, infrared or multispectral imaging techniques, and machine learning-based methods. Below, we explore the relevant work along with their respective advantages and limitations.

**Traditional Approaches in Cotton Production** Traditionally, foreign fiber cleaning has relied on manual inspection and mechanical separation techniques (Adeleke 2023). However, it is highly labor-intensive and prone to human error, especially as the volume of cotton increases. Additionally, the consistency of manual inspection is difficult to maintain, as worker fatigue and variability in experience can lead to missed contaminants (Tausif et al. 2018). Mechanical separation methods, such as ginning and centrifugal force separation, use physical properties like size, shape, or density to separate foreign fibers from the cotton (Van der Sluijs and Hunter 2017). While reducing manual labor, these

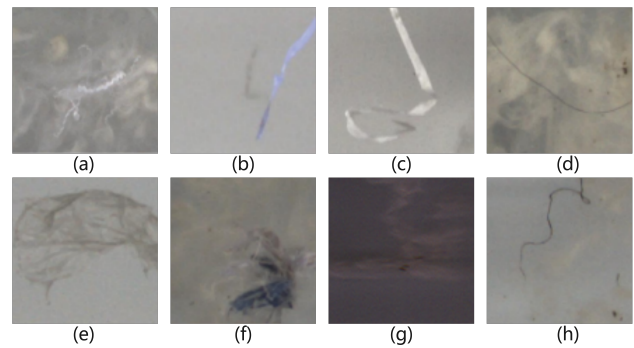


Figure 2: Samples of foreign fibres.

methods struggle to distinguish between small or similarly shaped contaminants and cotton fibers, limiting their effectiveness for high-quality separation.

**Multispectral Imaging Approaches** Infrared (IR) and multispectral imaging have emerged as promising technologies for detecting foreign fibers in cotton (Mustafic, Jiang, and Li 2016; Dian et al. 2021). These techniques leverage the differences in how various materials reflect or absorb light across multiple wavelengths, allowing for the identification of contaminants that may not be visually distinguishable (Zhang et al. 2016). The primary advantage of these imaging techniques is their ability to detect contaminants in a non-invasive manner and with high precision (Guo et al. 2012; Genser, Seiler, and Kaup 2020). However, the equipments for such techniques are often expensive and need specialized training to operate. The processing of spectral data can be computationally intensive, limiting the speed in real-time production settings (Xun et al. 2021). Despite these challenges, the potential for high accuracy makes these techniques valuable in cotton cleaning.

**Machine Learning Techniques** Recently, machine learning has revolutionized foreign fiber detection in cotton production. Machine learning models (Jiang and Li 2015), particularly deep vision techniques such as UNet, are trained on vast datasets of labeled images to automatically identify and classify foreign fibers (Tang et al. 2023). By learning from a large number of examples, these models can generalize well to unseen data, making them effective in diverse production environments (Vidit, Engilberge, and Salzmann 2023).

A key strength of machine learning approaches is their ability to improve over time as more data becomes available. Furthermore, machine learning models can be integrated with existing imaging technologies, such as multispectral imaging, to further enhance detection capabilities (Manavalan 2022). However, these models heavily depends on the quality and quantity of labeled training data. Additionally, the computational resources required to train and deploy these models can be significant, particularly for real-time applications in large-scale production environments. As the cotton industry continues to evolve, the integration of these advanced techniques will likely play a crucial role. Thus, we sought to design an AI-enabled hardware-software integrated system for foreign fiber detection.

## Our Approach in a Nutshell

To address the pressing challenge of detecting and removing foreign fibers in cotton production, we developed a comprehensive AI-enabled hardware-software integrated system. This system is designed to enhance the efficiency and accuracy of contaminant detection, thereby improving the overall quality of the cotton cleaning process.

### Overview of Our Approach

Figure 3 illustrates the workflow of our approach. It consists of three main stages. (1) Pre-Cleaning: This stage is responsible for removing impurities like soil and other non-fiber contaminants from the raw cotton. The cleaned cotton then serves as the input material for the next stage. (2) Foreign Fiber Detection: This is the core part of the system, where advanced imaging and machine learning algorithms are used to identify foreign fibers such as plastic films, hair strands, and polypropylene residues. The output from this stage is clean cotton, free from foreign fibers. (3) Packaging: This stage is primarily responsible for triggering electromagnetic valves based on the detected foreign fibers. Using air jets, the foreign fibers are swiftly removed from the cotton. After this sorting process, the cleaned cotton is packaged as the final product, ready for distribution or further use. These three parts work in sequence, ensuring that the cotton is thoroughly cleaned and prepared. We focus on Stages 1 and 2, as Stage 3 has already been developed by our collaborator.

### Pre-Cleaning (Stage One)

The first stage primarily focuses on removing large non-fibrous impurities from the raw cotton using mechanical principles. The system utilizes a combination of mechanical mechanisms such as vibrating screens, air jets, and gravity-based separators. Specifically, the cotton is first passed through vibrating screens that shake the raw material, causing heavier and larger particles such as stones, clods of dirt, and large debris to fall away from the lighter cotton fibers. Next, the cotton is subjected to airflow separation, where a controlled air current is used to blow away lighter impurities such as dust and fine dirt particles. The airflow is precisely calibrated to ensure that only contaminants are removed, while the cotton fibers remain intact and continue through the process. Gravity-based separation is also employed, where cotton fibers are dropped through a series of chambers that allow heavier impurities to be separated from the lighter fibers due to gravitational forces. This helps further eliminate any remaining large impurities that could potentially interfere with the following foreign fiber detection.

### Foreign Fiber Detection System (Stage Two)

The second stage utilizes different light sources to illuminate the cotton and identify foreign fibers based on their imaging characteristics. Figure 4 illustrates the 3-D CAD and prototype of the foreign fiber detection, highlighting the design and functionality of our system.

**Line-Scan Camera Imaging Module** The core of our hardware is a line-scan camera, which captures continuous images of cotton fibers as they move along a conveyor belt.

In our system, the line-scan camera is paired with three distinct light sources: white light, red laser, and green laser.

The white light source is used to illuminate the cotton fibers and is particularly effective for detecting colored foreign fibers, such as threads, plastic, or other materials that differ significantly in color from the cotton itself. The red and green lasers are specifically designed to detect low-contrast contaminants, such as white plastic films or other materials that closely resemble the color of cotton fibers. These laser light sources create distinct reflections and enhance contrast in the captured images, making it easier to differentiate between the cotton fibers and the contaminants.

As shown in Figure 5, under the condition of a fixed laser wavelength and light power, the average gray difference between foreign fibers and the cotton background in the image reaches a maximum as the imaging exposure time increases. Additionally, for different laser power levels, the required imaging exposure time to reach the maximum average gray difference varies: the higher the power, the shorter the required exposure time to reach the maximum, and vice versa. In production, shorter imaging exposure times are advantageous for improving detection speed. Thus, the optimal laser power should achieve the peak average gray difference in the shortest possible imaging exposure time. In this experiment, the optimal power for green laser (405 nm) was 70 mW, and for red laser (658 nm) was 55 mW.

The red laser (658 nm) exhibited the highest peak in the average gray difference curve and required the shortest imaging exposure time to reach this peak. The height of the peak in the average gray difference reflects the strength of the image contrast: the larger the average gray difference, the stronger the image contrast, making it easier to distinguish foreign fibers from the cotton background. Based on this, the optimal imaging parameters under the conditions of this experiment are: wavelength 658 nm (red light), power 55 mW, and imaging exposure time of 36 s.

**Field Correction and Calibration Algorithm** To ensure consistent image quality across different production environments, the line-scan camera is equipped with a sophisticated field correction software module. This module adjusts for variations in lighting, camera angles, and other environmental factors that could affect image quality. The field correction process ensures that the captured images are uniform and accurate (Blaschitz, Štolc, and Antensteiner 2018; Yuan et al. 2021). This consistency is crucial for reliable contaminant detection, as it minimizes the risk of false positives or missed contaminants due to image quality issues.

First, capture a set of calibration images with known geometric patterns, such as a checkerboard or dot grid. These calibration images typically contain a series of parallel lines or dots that should ideally remain straight in the image. Based on the calibration images, analyze the distortion effects in the camera's imaging to calculate the distortion parameters of the line-scan camera. Distortion is usually categorized into two types: radial distortion and tangential distortion. Radial distortion causes straight lines to appear curved, especially towards the edges of the image. The corrected coordinates  $(x_c, y_c)$  of a distorted point  $(x, y)$  can be

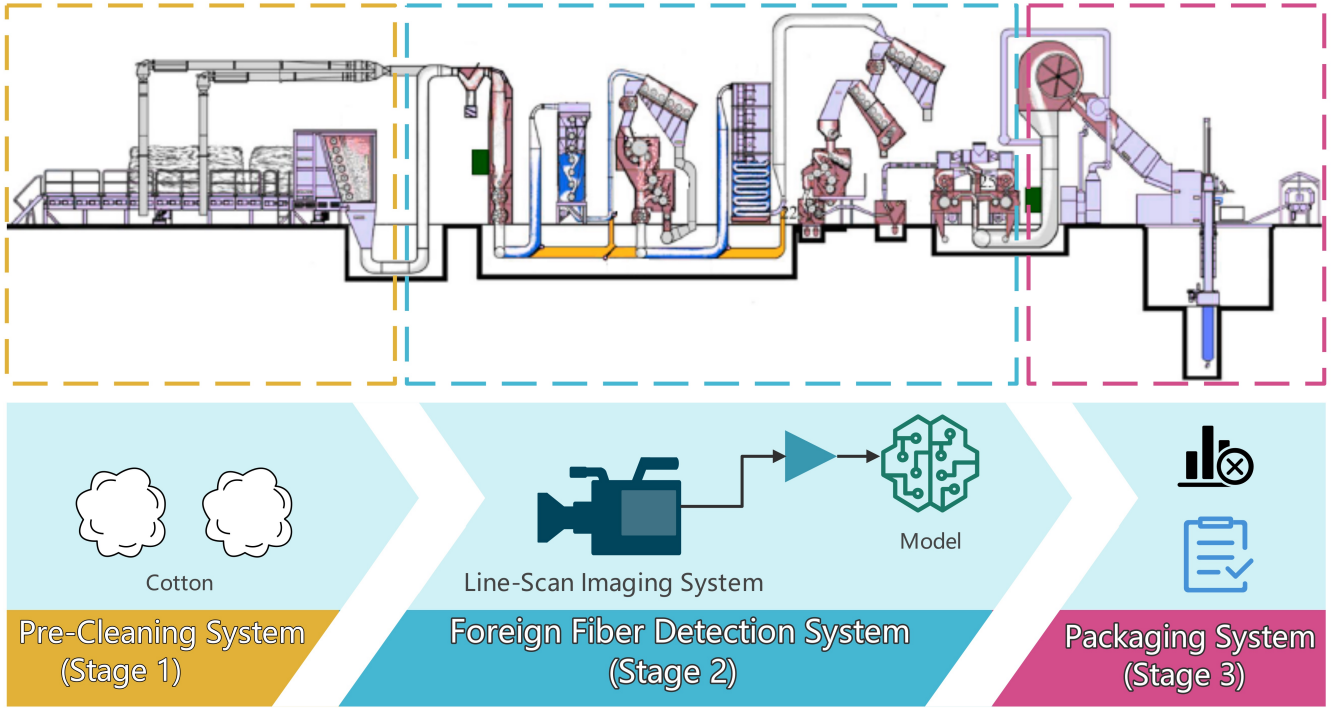


Figure 3: The workflow of our AI-enabled hardware-software integrated system. The section within the blue box represents our foreign fiber cleaning machine (Figure 1.b), with its entire internal process and structure laid out on a flat plane.

calculated using the following formula:

$$x_c = x (1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \quad (1)$$

$$y_c = y (1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \quad (2)$$

where  $r$  is the distance from the image center, and  $k_1$ ,  $k_2$ , and  $k_3$  are the radial distortion coefficients.

Tangential distortion occurs when the lens and the image sensor are not perfectly aligned. The corrected coordinates can be calculated as:

$$x_c = x + [2p_1 xy + p_2(r^2 + 2x^2)] \quad (3)$$

$$y_c = y + [p_1(r^2 + 2y^2) + 2p_2 xy] \quad (4)$$

where  $p_1$  and  $p_2$  are the tangential distortion coefficients. This step ensures that the camera is properly calibrated and the images are geometrically accurate.

**Few-shot Foreign Fiber Detection Network** To address the challenge of detecting foreign fibers in cotton with limited samples, we modify and introduce the CLIP model (Zhou et al. 2023) to achieve few-shot foreign fiber detection (FSFFD). As illustrated in the Figure 6, FSFFD first incorporates object-agnostic text prompt templates. Specifically, we design two general templates: NT (Normal Template) and AT (Anomaly Template). NT represents the absence of foreign fibers, while AT represents their presence. These templates are used to learn generalized embeddings for the normal and abnormal classes, respectively.

To improve textual embedding learning for foreign fiber discrimination, we introduce prior semantic knowledge into

the text prompt templates (Strobel et al. 2022; Zhou et al. 2023). Let  $n_t = [V_1][V_2] \dots [V_E][\text{Cotton}]$  and  $a_t = [W_1][W_2] \dots [W_E][\text{foreign fiber}][\text{Cotton}]$ , where  $[V_i]$  and  $[W_i]$  (for  $i \in \{1, \dots, E\}$ ) represent learnable word embeddings in the with/without foreign fiber text prompt templates, respectively. The learnable embeddings  $[V_i]$  correspond to the cotton without foreign fiber, while  $[W_i]$  correspond to the cotton with the additional foreign fiber-specific token *foreign fiber*. This approach reduces the need for extensive manual engineering of text prompt templates. We refer to the text prompts developed through this method as object-aware text prompts. To effectively learn object-agnostic text prompts, we employ a joint optimization method that refines the prompts from both global and local perspectives. During training, all modules are jointly optimized using a combination of global and local context optimization strategies,  $L_{\text{total}}$ :

$$L_{\text{total}} = L_{\text{global}} + \lambda \sum_{M_k \in M} L_{\text{local}}^{M_k}, \quad (5)$$

where  $\lambda$  is a hyperparameter that balances the global and local losses.  $M$  denote the set of intermediate layers used,  $M = |M|$ .

The global context optimization, utilizing a cross-entropy loss, ensures that our object-agnostic text embeddings are aligned with the global visual embeddings of images containing various foreign fiber. This alignment helps capture normal and abnormal semantics from a global feature perspective. Let  $S \in \mathbb{R}^{H_{\text{image}} \times W_{\text{image}}}$  be the ground-truth segmentation mask, where  $S_{j,k} = 1$  if the pixel is a foreign fiber and

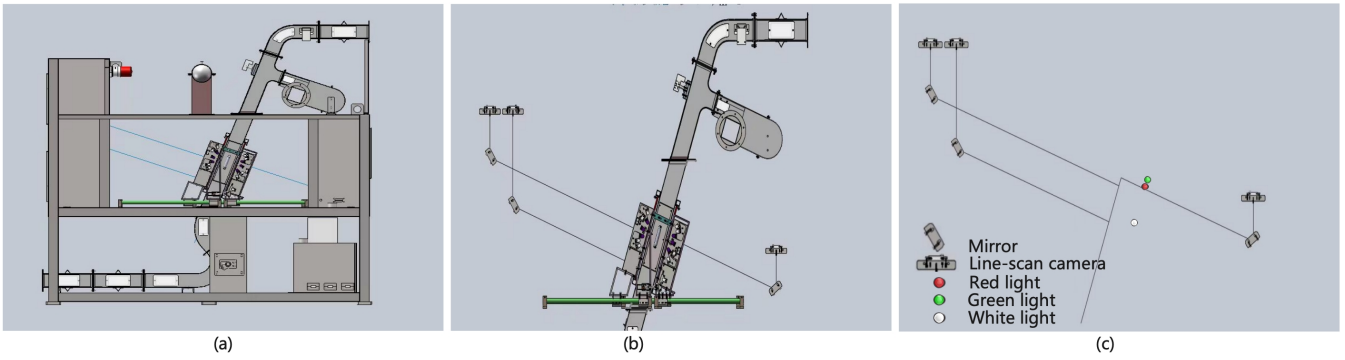


Figure 4: The Advanced Imaging and Foreign Fiber Detection System: a) the side view of the system’s 3D CAD design.; b) the positions of the cameras and light sources; and c) the optical path of our system directs light from the source, reflects it through mirrors, and then to the camera.

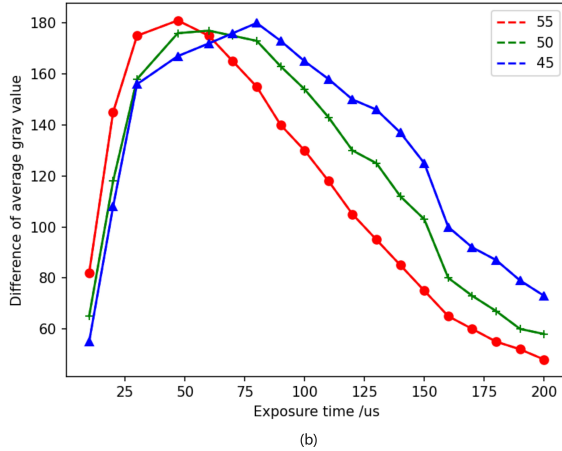
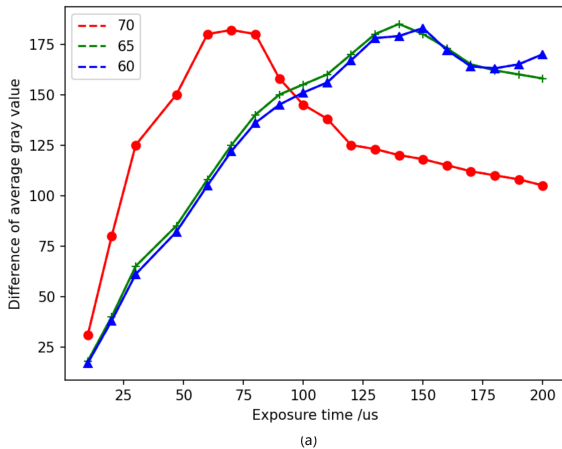


Figure 5: The average grayscale difference curves under different laser wavelengths with varying illumination and exposure conditions.: a) the green laser; and b) the red laser;

$S_{jk} = 0$  otherwise. The global loss can be expressed as:

$$L_{\text{global}} = -\frac{1}{N} \sum_{j=1}^H \sum_{k=1}^W [S_{jk} \log P(nt, f_{i, M_k}(j, k)) + (1 - S_{jk}) \log P(at, f_{i, M_k}(j, k))], \quad (6)$$

where  $P(nt, f_{i, M_k}(j, k))$  and  $P(at, f_{i, M_k}(j, k))$  denote the similarity scores between the foreign fiber and normal text embeddings and the visual embeddings, respectively.

On the other hand, the local context optimization allows object-agnostic text prompts to focus on fine-grained, localized abnormal regions detected by multiple intermediate layers of the visual encoder. This approach complements the global feature learning by providing detailed local information. The local loss  $L_{\text{local}}^{M_k}$  is defined as:

$$L_{\text{local}}^{M_k} = \text{Focal}(U_p(S_n, M_k), S) + \text{Dice}(U_p(S_n, M_k), I - S) + \text{Dice}(U_p(S_a, M_k), S), \quad (7)$$

where  $\text{Focal}(\cdot, \cdot)$  (Lin et al. 2017) and  $\text{Dice}(\cdot, \cdot)$  (Zhao et al. 2020) represent the focal loss and Dice loss, respectively. The operators  $U_p(\cdot)$  and  $[\cdot, \cdot]$  denote upsampling and concatenation along the channel, and  $I$  is the full-one matrix.

For inference, when presented with a test image  $x_i$ , we use the similarity score  $P(t_e, v_e)$  as the image-level foreign fiber score. The score approaches one when the textual embedding  $t_e$  aligns closely with the global visual embedding  $v_e$ . For pixel-wise predictions, we merge the segmentations and from all selected intermediate layers to obtain the final results.

## Experiments

### Datasets

We utilized our developed line scan camera module to continuously capture images during actual production, resulting in a substantial dataset of over 10,000 photographs. Among these, approximately 3000 images contain foreign fibers. Each photograph has a resolution of  $4096 \times 200$  pixels, providing high-detail captures of the cotton passing through the

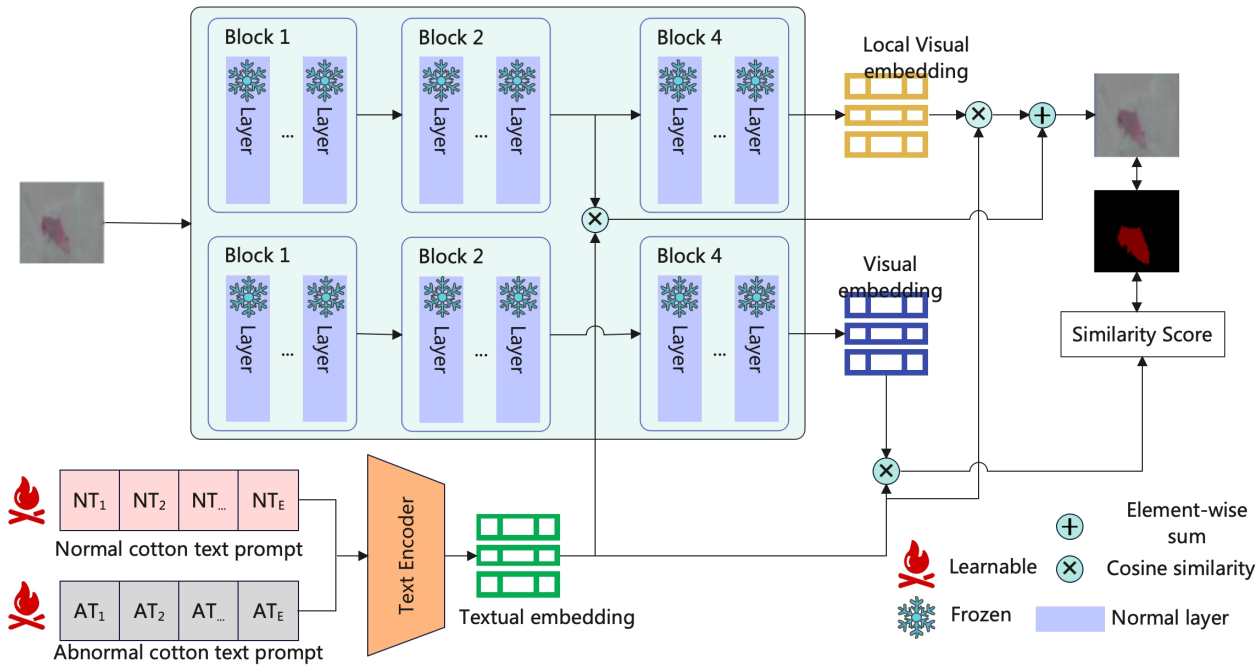


Figure 6: The framework of few-shot foreign fiber detection network.

production line. The cotton is conveyed on a conveyor belt at a speed of 8 meters per second. This high-speed movement allows for the acquisition of numerous images in a short period, which is crucial for robust data collection and accurate foreign fiber detection.

In our experimental setup, we first apply the default normalization provided by CLIP across all datasets. Following normalization, we divide each  $4096 \times 200$  image into 20 smaller images. After this division, we assign pixel-wise annotations to each of the resulting images. Since the 3,000 images are private assets of Zhongmian, we randomly selected 100 images from the set and uploaded them to the following link: <https://doi.org/10.6084/m9.figshare.27934695.v1>

## Comparisons

Table 1 presents a comparison of our method with other established approaches on the collected dataset. The metrics used for comparison include accuracy (Acc) and Intersection over Union (IoU), both of which are standard evaluation metrics for assessing the performance of detection and segmentation tasks. The methods are as follows:

**SVM** : A traditional machine learning approach uses Support Vector Machines. It achieved an accuracy of 70.3% and an IoU of 56.3%, which indicates moderate performance on the dataset.

**UNet** : A deep learning model are widely used in segmentation tasks. UNet showed improved results over SVM, with an accuracy of 77.2% and an IoU of 61.9%.

**CLIP** : A method leverages the powerful visual-textual embeddings from the CLIP model. It further improves the accuracy to 83.2% and the IoU to 63.8%, demonstrating its ability to align textual and visual features effectively.

Method	Acc	IoU
SVM (Jiang and Li 2015)	70.3	56.3
UNet (Tang et al. 2023)	77.2	61.9
CLIP (Rasheed et al. 2023)	83.2	63.8
<b>Ours</b>	<b>92.9</b>	<b>86.2</b>

Table 1: Comparisons with other methods on our dataset.

**Ours (XCotton)** : Our approach significantly outperforms the other methods, with an accuracy of 92.9% and an IoU of 86.2%, highlighting the effectiveness of our method in leveraging both global and local context optimization to detect foreign fibers in cotton more accurately.

This comparison demonstrates that our method provides a substantial improvement in both accuracy and segmentation quality (as measured by IoU) compared to traditional and state-of-the-art approaches.

Table 2 provides insight into the effectiveness of the two key modules—global and local context optimization. These modules are driven by object-agnostic prompt learning, which is central to our approach and is formulated with the global context optimization strategy. Specifically, the table illustrates how different configurations of global and local losses contribute to the performance of our model.

(1) No Local and No Global (X X): Without any optimization, the model achieves an accuracy of 83.2% and an IoU of 63.8%, offering a baseline where neither global anomaly semantics nor localized features are explicitly captured.

(2) Global Only (X ✓): Introducing global context optimization enhances performance to 86.1% accuracy and 69.2% IoU. This improvement underscores the role of global context optimization in capturing broad anomaly semantics,

Local	Global	Acc	IoU
✗	✗	83.2	63.8
✗	✓	86.1	69.2
✓	✗	88.7	75.3
✓	✓	92.9	86.2

Table 2: Ablation study for different configurations of our method on the collected dataset.

which bolsters image-level detection accuracy.

(3) Local Only (✓ ✗): In contrast, employing only local context optimization yields even better results, with accuracy climbing to 88.7% and IoU reaching 75.3%. This shows the importance of capturing fine-grained local anomaly features, which not only improve pixel-level performance but also complement image-level detection.

(4) Both Local and Global (✓ ✓): The best results—92.9% accuracy and 86.2% IoU—are achieved when both global and local context optimization strategies are combined. By synthesizing these two strategies, the model captures both global and local anomaly semantics, leading to superior performance at both image and pixel levels.

The ablation study highlights the importance of global and local context optimization in the overall performance of our method. Global optimization enhances image-level detection by capturing foreign fiber features, while local optimization improves pixel-level accuracy by focusing on detailed local features. Together, these strategies make our model more effective in detecting foreign fibers, especially when both optimizations are employed simultaneously.

### Computation complexity

As shown in Figure 6, we selectively fine-tune only the designed prompt templates while freezing the parameters of the other layers. This approach significantly enhances computational efficiency, even with the inclusion of both global and local loss functions. Despite the added complexity, our model processes images rapidly, handling 20 images with a resolution of  $4096 \times 200$  pixels efficiently. This speed ensures that our entire machine setup meets the demands of real-world cotton production in terms of both efficiency and output. Additionally, this design reduces the computational overhead and allows for real-time processing, which is crucial for maintaining the high throughput required in industrial cotton processing environments. This balance between computational efficiency and performance makes our system both practical and scalable for large-scale applications.

### Deployment

We worked with ZhongMian to deploy our AI-enabled hardware-software system. ZhongMian is one of the leaders in manufacturing automated cotton cleaning machines. Figure 7 illustrate the ready-to-ship product of the machine equipped with XCotton, which has been fully integrated into the client’s cotton production line. This method involves installing XCotton’s hardware and software components, configuring them for optimal performance, and ensuring that the system operates seamlessly in the production environ-

ment. For clients with existing machinery, we provide customized deployment of XCotton in their current equipments. The modular deployment approach is designed to be cost-effective, particularly for clients who already have a robust production setup. By integrating only the specific components of XCotton that enhance their existing systems, we help our clients avoid the expenses associated with a complete overhaul of their equipment.



Figure 7: The equipments are ready for shipping to clients in Africa and Central Asia via sea and rail transport.

So far, XCotton has been successfully deployed in 100 cotton processing enterprises, mostly in developing countries such as China, Central Asia, and Africa. In China, our system has been integrated into numerous local cotton processing facilities, contributing to enhanced production efficiency and improved cotton quality across the industry. Similarly, our deployments in Central Asia and Africa have supported local cotton producers by modernizing their operations and increasing their competitiveness in the global market. We have received positive feedback from our clients. They have reported that XCotton has significantly improved their production processes and overall efficiency.

### Technical Improvements

Our machine delivers significant improvements across almost all critical performance metrics (Table 3). It provides 1.4x cotton processing capacity, while reducing energy consumption by over 60%, and enhances cleaning efficiency by lowering impurity rates. With advanced foreign fiber recognition capabilities, the system operates with a high level of accuracy and stability, even under varying production conditions. The reduction in noise levels contributes to a better working environment, while the accelerated processing ensures system responsiveness. Overall, XCotton does not only drive higher production efficiency but also result in considerable cost savings in energy and labor, while enhancing product quality and operational sustainability.

### Business Impacts to ZhongMian

ZhongMian started manufacturing and shipping the new lint cleaning machines (XCotton) from the second half of 2023. Since 2024, the number of XCotton being built has exceeded the number of traditional machines (56 vs. 41) (see Table 4). It has significantly improved ZhongMian’s profitability under a more competitive market in 2024. The gross profit per machine has seen a remarkable increase, reflecting higher product value and better market positioning. Revenue and gross profit for 2024 have grown substantially, driven

Metrics	Traditional (before deploy.)	XCotton (after deploy.)
Processing Capacity	$\leq 700$ kg/h	$\geq 1000$ kg/h
Recognition Rate	Plastic: 0% Other: $\leq 65\%$	$\geq 90\%$
Energy Consumption per 100kg	$\geq 4.1$ kWh	$\leq 1.5$ kWh
Impurity Cotton Rate	$\geq 40\%$	$\leq 25\%$
Recognition Accuracy Fluctuation Range	NA	$\leq 5\%$
Processing Time per Image	NA	$\leq 1$ ms
Noise Level	$\geq 90$ dB	$\leq 65$ dB

Table 3: Technical metrics and comparisons.

by strong demand for the new machines, which has out-paced sales of traditional models. The growing order backlog further indicates a robust market interest and a shift towards more efficient, AI-enabled machinery. These results highlight the successful commercial impact of the new machines, with substantial improvements in both financial performance and customer adoption.

Metrics	Traditional (before deploy.)	XCotton (after deploy.)
Cost/Machine *	0.2 Million	0.33 Million
Price/Machine	0.3 Million	0.45 Million
Gross Profit/Machine	0.1 Million	0.12 Million
2024 sales by 8/15	41 machines	56 machines
2024 Revenue by 8/15 (estimated)	12.3 Million	25.2 Million
2024 Gross Profit by 8/15 (estimated)	4.1 Million	6.72 Million
Order Backlog (Quantity)	21	39
Order Backlog (Value)	6.3 Million	17.55 Million

Note. \*: The cost for manufacturing individual machines may vary due to small adaptations to clients' needs and production environment. The cost and the following metrics here are average estimations.

Table 4: Business-related metrics and comparisons (all values are in CNY-Chinese Yuan).

### Impacts on LDCs' Cotton Fabric Industry

With precise cleaning and processing capabilities, our system ensures that the cotton produced is of a higher grade. This enhancement in quality improves the competitiveness of cotton products from LDCs on the global stage, potentially leading to increased revenues and better trade opportunities for these regions (Figure 8). ZhongMian's clients had described and discussed their benefits with ZhongMian. Let us take the clients from Sudan (an African country) as an example. Their traditional lint cleaning equipment were mostly produced during 1970s. Such equipment has severely exceeded the service life and led to high maintenance cost. By 08/31/2024, six new machines have been shipped to Su-

dan, and nine new machines are in the order backlog. According to our clients, one new machine could reduce about 70 human cleaning workers manual labor, saving about 0.5 million CNY labor cost annually. The annual savings on the labor cost and maintenance cost have been much more the cost of purchasing and installing a new machine. More importantly, it helps to move the human labors from the low-end cotton fabric production to high-end manual jacquard production, facilitating the industry upgrade and improve human workers' incomes.



Figure 8: Our clients from Africa.

ZhongMian has been continuously working on introducing the XCotton to clients in LDCs. For example, ZhongMian had participated the 8th CHINA-EURASIA Expo and showcased the XCotton system. It received many interested inquiries and potential orders from clients in Central Asia. The strong interest reflects the growing demand for advanced technologies in the industry and highlight the potential for future collaborations and expansions. We are enthusiastic about the opportunities to work with clients from LDCs, further realizing the broader impacts of our AI-enabled solution.

### Conclusion

In this paper, we present XCotton, an innovative AI-enabled hardware/software co-design for automated lint cleaning in cotton fabric production. XCotton has been successfully manufactured and deployed, showcasing its effectiveness in enhancing production efficiency and quality. Our system significantly reduces the manual effort required for contaminant removal in cotton processing, streamlining operations and improving overall productivity. This advancement not only helps ZhongMian enhance its profit margins and solidify its leadership position in the industry but also empowers its clients in LDCs to modernize their cotton fabric industries. By adopting XCotton, these clients can gain a competitive edge in the global value chain, leading to improved economic outcomes and enhanced capabilities in the international market. Thus, XCotton represents a significant step forward in cotton processing technology, with far-reaching benefits for both industry leaders and emerging markets.

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