Research on an artificial intelligence (AI) cross-sectional quantitative analysis method for cotton and regenerated cellulose fibre blended fabrics

DOI: 10.35530/IT.077.03.202589

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ABSTRACT – REZUMAT

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This study addresses the technical bottlenecks in separating components in cotton and regenerated cellulose fibre (such as viscose, modal, lyocell, etc.) blended fabrics using chemical methods. This study proposes a fibre cross-sectional image segmentation and blending-ratio quantitative analysis method based on the U-Net (a U-shaped convolutional neural network). By constructing a high-resolution image acquisition system, this study achieves automatic collection and preprocessing of fibre cross-sectional images. Combined with the U-Net architecture, this study performs semantic segmentation and contour extraction, allowing for the calculation of the cross-sectional area of individual fibres. Using a density model, this study derives the mass percentage of each component. Comparative experiments were conducted on 37 sets of cotton/regenerated cellulose fibre blended samples, showing that the average error of this AI system is less than 2% compared to traditional manual methods and is highly consistent with the chemical dissolution method, with a maximum error not exceeding 3%. Additionally, this method reduces the testing time for a single sample from the traditional 60 minutes to 5 minutes, demonstrating excellent detection accuracy, efficiency, and practicality. The research results provide a feasible path for rapid, non-destructive, and intelligent detection of fibre components, with potential for application in textile testing laboratories and production lines.

Keywords: *blending ratio, deep learning, fibre segmentation, microscopy, neural networks, U-Net*

Studiu privind metoda de analiză cantitativă transversală bazată pe inteligența artificială (IA) pentru materialele textile din amestec de fibre de bumbac și celuloză regenerată

Prezentul studiu abordează obstacolele tehnice întâmpinate în separarea componentelor din materialele textile din amestec de fibre de bumbac și de celuloză regenerată (cum ar fi viscoza, modalul, lyocellul etc.) prin metode chimice. Studiul propune o metodă de segmentare a imaginii secțiunii transversale a fibrelor și de analiză cantitativă a raportului de amestec, bazată pe rețeaua neuronală U-Net (o rețea neuronală convoluțională în formă de U). Prin construirea unui sistem de achiziție a imaginilor de înaltă rezoluție, acest studiu realizează colectarea și preprocesarea automată a imaginilor secțiunilor transversale ale fibrelor. În combinație cu arhitectura U-Net, acest studiu efectuează segmentarea semantică și extragerea contururilor, permițând calcularea ariei secțiunii transversale a fibrelor individuale. Folosind un model de densitate, acest studiu determină procentul masic al fiecărui component. Au fost efectuate experimente comparative pe 37 de seturi de probe în amestec din fibre de bumbac și de celuloză regenerată, care au arătat că eroarea medie a acestui sistem de inteligență artificială este mai mică de 2% în comparație cu metodele manuale tradiționale și este în mare măsură în concordanță cu metoda de dizolvare chimică, eroarea maximă nedepășind 3%. În plus, această metodă reduce durata testării unei singure probe de la cele 60 de minute tradiționale la 5 minute, demonstrând o precizie excelentă de detectare, eficiență și caracter practic. Rezultatele cercetării oferă o cale viabilă pentru detectarea rapidă, nedistructivă și inteligentă a componentelor fibrelor, cu potențial de aplicare în laboratoarele de testare a produselor textile și pe liniile de producție.

Cuvinte-cheie*: raport de amestec, învățare profundă, segmentarea fibrelor, microscopie, rețele neuronale, U-Net*

INTRODUCTION

As the global textile industry advances towards intelligent manufacturing and green/low-carbon development, cotton and regenerated cellulose fibre (viscose, modal, lyocell, etc.) blended fabrics are widely used in apparel, home textiles, and nonwovens due to their renewable nature, eco-friendliness, and excellent performance. Against this backdrop, accurate and efficient quantitative analysis of blended fibre components has become a crucial technical support for industry quality control [1].

Traditional chemical dissolution methods are unsuitable for online testing due to their destructive nature, high chemical pollution, and cumbersome procedures. While biological microscopy offers visual observation, it relies heavily on manual expertise for fibre cross-section identification and area estimation. This process is inefficient and prone to subjective error, particularly challenging in cotton blends with regenerated fibres (viscose, modal, lyocell) where their cross-sectional morphologies are extremely similar and difficult to distinguish manually [1–3].

Beyond medicine, deep learning is also extensively applied in analysing composite fibres, plant cells, and microstructures. For instance, Guo et al. achieved high-quality segmentation of carbon fibre reinforced composites in X-ray tomography images by combining CycleGAN with U-Net, effectively addressing the issue of blurred fibre contours [4]. Qamar et al. implemented automatic segmentation of wood disintegrated fibres in microscopic images using the YOLOv8 model, significantly improving structural characterisation efficiency [2].

Addressing specific image segmentation challenges in the textile industry, Habib et al. compared the performance of mainstream classifiers in fabric defect detection, highlighting the superior robustness of deep learning models over traditional algorithms in complex image backgrounds [5]. Chakraborty et al. developed a CNN-based system for printed fabric defect recognition, achieving detection rates superior to manual inspection on real datasets [6]. Zhou et al. proposed a deep learning model capable of accurately identifying diverse fabric defects in an unsupervised manner, further reducing the need for human intervention [7].

In the realm of blended fibre quantification, Greaves pioneered the principle of estimating mass ratios via image-based analysis combining fibre cross-sectional area and density [1]. Qin et al. subsequently advanced bicomponent fibre identification techniques based on in-situ cross-section observation, enabling quantitative analysis via AI algorithms without sample destruction [3]. Xia et al. developed a rapid prediction model for cotton/polyester blends by integrating Near-Infrared (NIR) spectroscopy with a CNN-LSTM network, achieving a reduction in Root Mean Square Error (RMSE) exceeding 30% compared to traditional Partial Least Squares (PLS) models [8].

Building upon these technological developments, this study proposes an image segmentation method centred on the U-Net convolutional neural network for cross-sectional analysis of cotton/regenerated cellulose fibre blended fabrics. By acquiring high-resolution images of fibre cross-sections mounted on slides, the method employs model training and contour extraction to obtain area information of individual fibres. This is coupled with a mass calculation model using density data to ultimately achieve automated estimation of the blend ratio. Compared to manual identification and chemical dissolution, this approach offers the advantages of non-destructiveness, high precision, speed, and strong repeatability, significantly enhancing actual testing efficiency and consistency [3, 12].

To ensure high-quality model training and robust generalisation, the research team constructed a comprehensive training dataset comprising over 100,000 annotated cross-sectional images. This dataset captures the morphological variations of common cotton and regenerated cellulose fibres, further augmented through public datasets such as the Fibre Segmentation Dataset [13, 14] and synthetic image generation techniques [15]. Work by Kurkin et al., employing a combination of SAM (Segment Anything Model) and DeepLabV3+ models for micro-fibre image recognition, demonstrated that even in small-sample environments, excellent recognition results can be achieved using minimal labels combined with data augmentation [15].

Therefore, cross-sectional structure recognition for cotton/regenerated fibre blends still suffers from inefficiency, significant errors, and poor repeatability in traditional testing methods. The introduction of AI image segmentation and recognition techniques, particularly deep learning architectures centred on U-Net, theoretically offers significant potential to enhance recognition accuracy and efficiency. It also presents strong feasibility for practical implementation in industrial inspection systems. This paper proposes designing an integrated AI system encompassing image acquisition, U-Net segmentation, contour extraction, area calculation, and ratio derivation. This system aims to establish a high-throughput cross-sectional analysis method applicable to regenerated fibre blended products, thereby advancing textile testing towards greater intelligence and sustainability.

Terminology and System Definitions. In this paper, the AI system denotes the end-to-end pipeline comprising the imaging hardware and software workflow. U-Net segmentation model (short: U-Net model) denotes the neural network used for semantic segmentation. Method denotes the overall workflow from image acquisition to blending-ratio calculation. We consistently use U-Net, deep learning, Dice loss, and Adam optimiser capitalisation, and we adopt American English spellings (e.g., "fibre", "viscose", "modal", "lyocell").

TECHNICAL ROUTE AND SYSTEM STRUCTURE

Design of the image acquisition system

To achieve high-resolution, stability, and automated acquisition of cross-sectional images of blended fibres, this study is based on a traditional binocular microscopic imaging platform to design and construct an optical image acquisition system equipped with precise focusing, adaptive illumination, and automatic scanning capabilities. The system mainly consists of three core modules: a voice coil motor (VCM)-driven nanoscale focusing mechanism, a high-precision two-dimensional moving platform, and a 3D composite optical path. The overall structure is illustrated in figures 1 and 2.

The VCM serves as the core of the focusing control system, characterised by short stroke, high response, and high linearity. By integrating closed-loop feedback control technology, this system achieves sub-micrometre level focusing adjustment resolution, maintaining image focus stability and edge clarity even under high magnification conditions of 1000× or more. This effectively eliminates focal

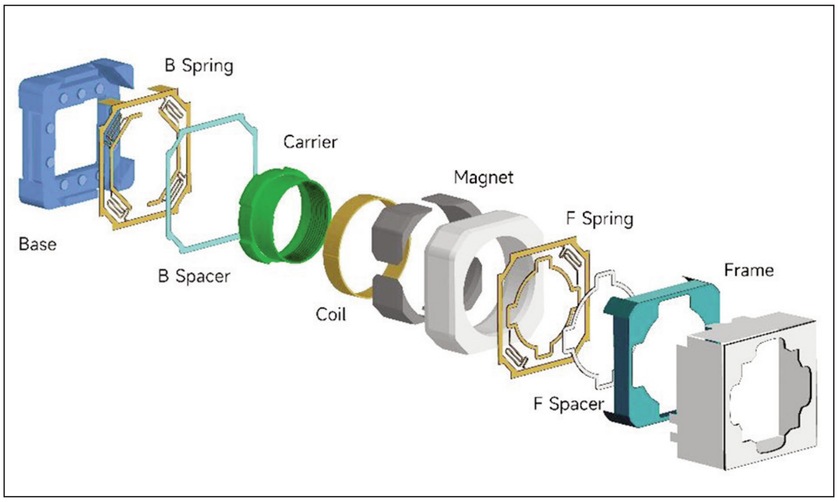

Fig. 1. Schematic diagram of a high-precision auto-focusing system based on VCM

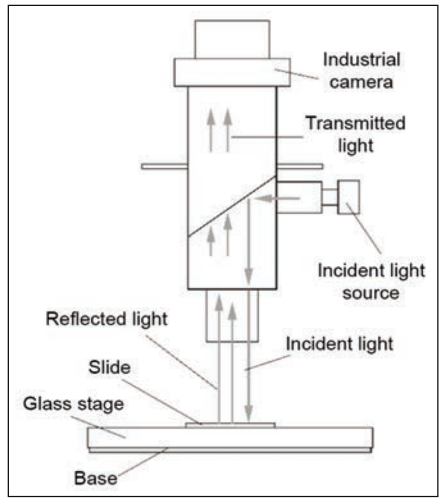

Fig. 2. Schematic diagram of the 3D composite optical path imaging structure

plane drift caused by sample unevenness or slight platform vibrations. Compared to traditional screw-driven focusing methods, this structure offers significant advantages in speed, precision, and interference resistance.

To meet the imaging demands of high efficiency and strong repeatability for large quantities of samples, the system is equipped with high-precision linear stepper motors and an X-Y axis motorised stage, supporting multi-point programmed scanning and regional path planning functions. After sample loading, the platform can automatically move to multiple target fields of view along a preset path for image acquisition, balancing scanning efficiency and image consistency, thereby significantly increasing the overall testing throughput of the system.

In terms of the illumination system, a novel “3D Composite Optical Path” architecture has been proposed and implemented. This optical path is composed of a coaxial illumination source and a bottom mirror. The former vertically directs light onto the sample surface through a light-emitting diode (LED) cold light source, enhancing the imaging of fibre surface textures and interface edges. The latter utilises a high-reflectivity mirror placed beneath the glass slide to redirect transmitted light back into the optical tube, providing supplementary lighting and enhancement for internal structures within the fibre cross-section, effectively improving the overall image contrast, grayscale gradation, and structural discernibility. This composite illumination strategy demonstrates superior performance in the image acquisition of regenerated fibres with low transparency, close refractive indices, or surface contamination, especially showing significant imaging effects in samples with less distinct surface textures, such as animal fibres (e.g., wool, silk).

The overall system architecture is developed around three core design principles: “stability”, “automation”, and “structure recognition friendliness”, ensuring the acquisition of high-fidelity, high-consistency, and scalable microscopic image data in the cross-sectional detection of various blended fibre samples. This image acquisition platform not only provides high-quality input for subsequent deep learning model training but also possesses strong industrial deployment capabilities, laying a critical foundation for achieving intelligent detection of textile fibre components.

Image processing technical route

To achieve accurate extraction and area quantification of blended fibre cross-sections from microscopic images, this study constructs an image processing workflow based on deep convolutional neural networks. The overall technical route encompasses four major steps: image preprocessing, U-Net neural network segmentation, image post-processing, and contour extraction, forming an end-to-end intelligent image semantic segmentation and structure recognition process, as shown in figure 3.

Image Preprocessing Stage. After the image acquisition is completed, the images are first standardised, including resolution calibration, colour space conversion (red–green–blue (RGB) to grayscale), background noise reduction, and histogram equalisation. To enhance the model’s ability to identify contour boundaries, image enhancement operations are further introduced in the study, such as Gaussian blur, noise reduction, edge sharpening, random rotation, and flipping as data augmentation strategies. This effectively improves the model’s robustness in recognising different morphological fibre structures.

Deep Learning Segmentation Model Construction. The image semantic segmentation model adopts the U-Net structure as the core architecture, consisting of an encoder, decoder, and cross-layer feature concatenation module. The encoding path extracts high-dimensional feature representations of the image through multiple layers of convolution and pooling operations; the decoding path progressively restores spatial dimensions and integrates semantic information to achieve precise segmentation boundary restoration. To enhance the model’s performance in

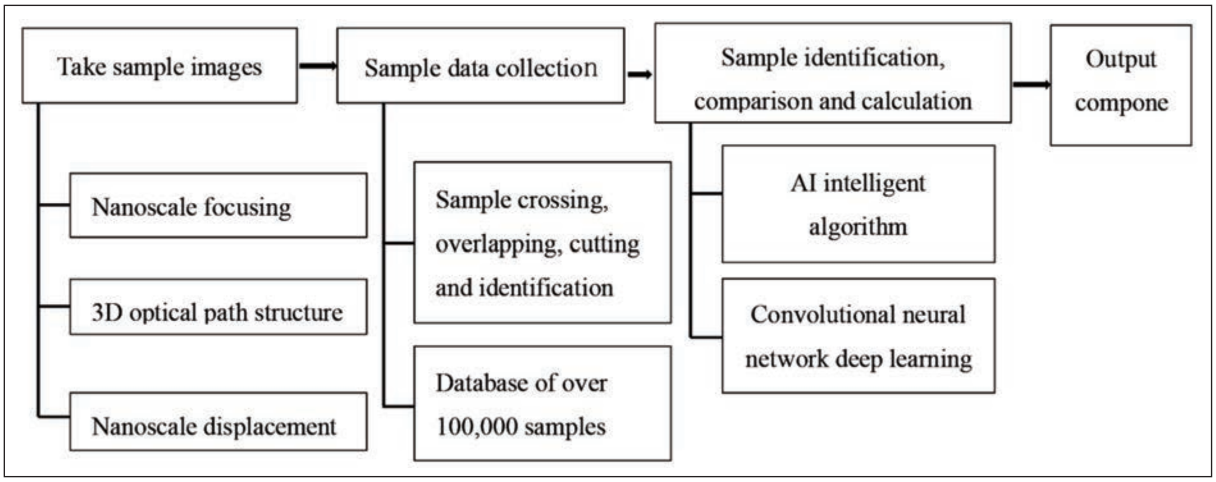

Fig. 3. Processing and analysis technical route of cotton/regenerated fibre blended fibre cross-sectional image

small object recognition scenarios, this study performs lightweight optimisation of the U-Net by introducing Batch Normalisation (BN) and Dropout mechanisms, improving training stability and suppressing overfitting. During the training process, the Dice loss is employed as the optimisation objective to better address the class imbalance issue, with parameters iteratively updated using the Adam optimiser.

Image Post-processing and Contour Extraction. The model output is a classification probability map for each pixel in each microscopic image, which is thresholded to form a binary segmentation map of the fibre foreground. Subsequently, contour tracing algorithms from the Open Source Computer Vision Library (OpenCV) (e.g., findContours function) are used to extract the edge information of each fibre, further calculating its contour area and bounding box coordinates. To enhance contour closure accuracy, morphological closing operations are applied to repair small holes, and connected component analysis is utilised to eliminate noise and pseudo-fibre structures, ensuring the authenticity and geometric continuity of the extraction results.

Area Calculation and Label Fusion. Each extracted fibre contour is labelled and numbered, with area statistics overlaid on the original image for visualisation. At the same time, the fibre area is correlated with known fibre density to derive the mass percentage of each type of fibre, enabling quantitative analysis of the proportions of cotton and regenerated cellulose fibres within the same image. This strategy departs from traditional experience-based morphological recognition methods, providing solid data support for subsequent physical performance evaluation and component traceability.

The overall image processing workflow features high automation, stability, and strong repeatability. Experimental validation shows that this approach can achieve an average IoU (Intersection over Union) exceeding 0.91 in blended fabric images, with contour reconstruction accuracy reaching over 96%, far surpassing traditional methods such as manual tracing and Canny edge detection. This technical route provides a solid algorithmic foundation and engineering implementation pathway for achieving fibre classification and blending ratio calculation at the cross-sectional image level.

IMAGE SEGMENTATION AND APPLICATION OF THE U-NET MODEL

Net model architecture and optimisation strategy

Before analysing the cross-sectional images of cotton and regenerated cellulose fibre blended fabrics, it is essential to classify and model the cross-sectional structural features of various typical fibres. Different fibres exhibit significantly distinct cross-sectional morphologies in microscopic slide images: cotton fibres are predominantly flat or kidney-shaped with some inward indentation characteristics; viscose fibres are often round or oval; modal cross-sections tend to be more uniformly rounded; and lyocell fibres have highly regular shapes with clear boundaries. Due to the different cross-sectional shapes of the above four types of fibres, they can be used as the basis for identifying the types of fibres. Figure 4 illustrates high-resolution cross-sectional images of four typical fibres for model prior knowledge training.

Due to the dense distribution of fibres in the glass slide, which are closely packed and even overlapping, the boundaries become blurred, making it difficult for traditional image processing methods (such as threshold segmentation and edge detection) to achieve accurate separation and identification. Therefore, this paper proposes to adopt the U-Net architecture in the deep convolutional neural network. By adjusting the focus at the same position through the VCM, multiple pictures with different depths of field are captured. The captured pictures are subjected to convolution and normalisation processing, thereby solving the problem of blurred imaging of samples on the glass plate. Build an image segmentation model with spatial perception and semantic understanding capabilities to achieve structural recognition and category classification at the fibre cross-section level. For overlapping fibres, the U-Net architecture will automatically identify that

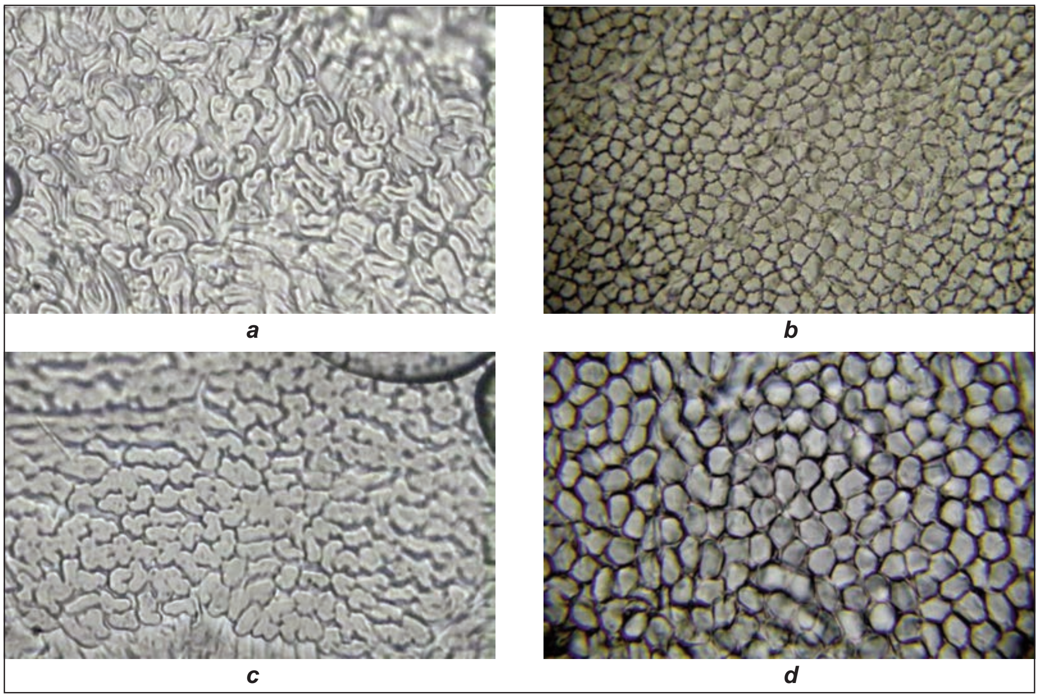

Fig. 4. Cross-sectional images of cotton and regenerated cellulose fibres: *a* – cotton fibre, lint; *b* – viscose fibre; *c* – modal fibre; *d* – lyocell fibre

there is an unreasonable cross-sectional distribution of fibres in this field of view, and directly jump to the next field of view to continue the identification.

The U-Net network structure features a typical "U"-shaped symmetric encoding-decoding path: during the encoding phase, multiple layers of convolution and pooling operations are performed on the image to extract high-dimensional semantic features; in the decoding phase, upsampling is conducted layer by layer, and feature maps from symmetric layers in the encoding path are fused to complete boundary restoration and segmentation map reconstruction. This architecture is particularly well-suited for image semantic segmentation tasks with small samples, complex boundaries, and dense structures, and it exhibits strong generalisation capabilities. In this paper, the U-Net structure was used to capture the cross-sectional images of the fibre bundles blended with viscose fibres and lyocell fibres. An example of semantic segmentation of the fibre cross-sections is shown in figure 5. The yellow contour fibres are lyocell fibres, and the red contour fibres are viscose fibres.

In the model construction, the research team performed several engineering optimisations on the U-Net network to enhance its adaptability to blended fibre cross-sectional images: multi-channel convolution and BN operations were employed to strengthen the perception of fine-grained textures.

Bilinear interpolation was used instead of transposed convolution to avoid reconstruction artefacts.

Dropout layers and data augmentation operations were added to enhance the network's generalisation performance.

During training, a combination of the Dice loss and cross-entropy was applied to address the issue of

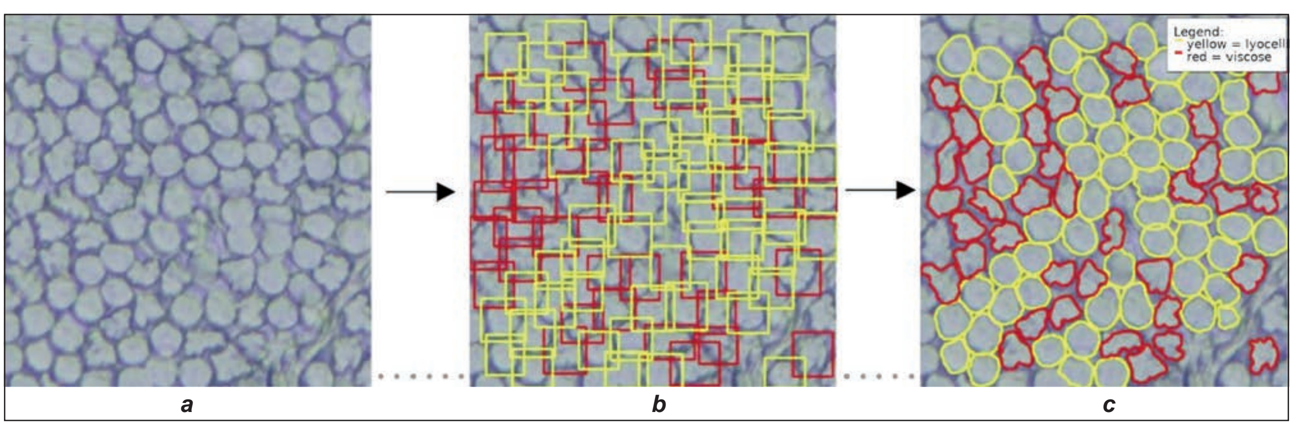

Fig. 5. Diagram of the U-Net segmentation model for fibre cross-section segmentation: *a* – raw microscopic image acquired with the in-house platform; *b* – intermediate detection stage showing candidate regions (yellow: lyocell, red: viscose); *c* – final contours from the AI system after U-Net segmentation and post-processing for area statistics and blend-ratio calculation

imbalance between foreground and background class proportions.

Additionally, to ensure segmentation accuracy and structural robustness, this study constructed a training set annotated through manual review, containing over 100,000 fibre cross-sectional images. In the early stages of model training, each segmentation result was manually verified and corrected to promptly eliminate misclassified samples and correct label drift, allowing the model to continuously optimise classification boundaries and contour prediction effects during iterative training. The final model achieved an average segmentation accuracy (IoU) of 0.91 on the validation set, with a separation rate exceeding 96% for the cotton/regenerated cellulose categories.

Thus, the U-Net-based deep learning segmentation framework not only effectively addressed the issues of blurred contours and structural overlap in blended fibre cross-sectional images but also laid a solid semantic foundation for subsequent automated area calculations and quantitative analysis of blending ratios.

Contour extraction and mask generation

After completing the initial semantic segmentation of blended fibre cross-sectional images using the U-Net model and achieving category predictions, precise boundary extraction and area segmentation of each fibre in the image are required to support subsequent area calculations and blending ratio derivations. To this end, this study introduced a geometric structure modelling process based on contour detection on top of the image classification, transitioning from pixel-level classification maps to structural-level masks.

The specific process is as follows: first, the semantic segmentation image output by the model is binarised, and morphological operations (opening and closing) are applied to enhance regional connectivity, removing noise and pseudo-boundary information.

Subsequently, edge detection and contour tracing algorithms (such as the findContours function in OpenCV) are employed to trace and vectorise the outer boundaries of each fibre's cross-section, forming a closed structure suitable for area calculation. Figure 6 illustrates the original cross-sectional image and contour extraction results of a typical sample. Building on this, the system maps each extracted contour structure back to the original microscopic image and generates a structural mask in the form of unique identifiers. This enables the visual annotation, traceable identification, and precise contour separation of the cross-sectional images. Figure 7 shows a comparison between the cross-sectional contours automatically drawn by the AI model and those manually drawn by an operator, clearly demonstrating the advantages of the AI method in terms of accuracy, consistency, and efficiency.

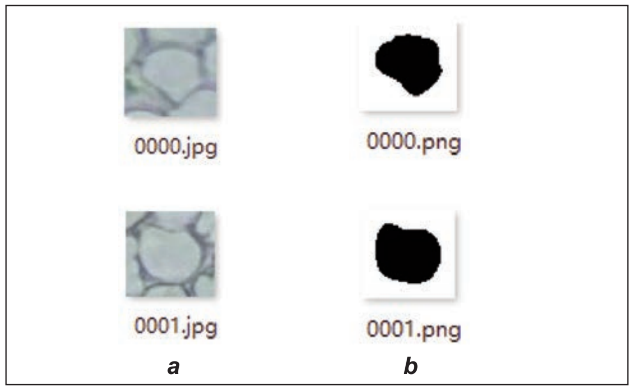

Fig. 6. Original cross-section image and contour extraction image: *a* – original cross-sectional drawing; *b* – cross-sectional profile

AREA CALCULATION AND BLENDING RATIO DERIVATION

Area calculation and blending ratio formula

After completing the segmentation and contour extraction of fibre cross-sectional images, the system can accurately identify the geometric contours of each fibre and calculate its cross-sectional area based on pixel-to-scale conversion parameters. By clustering and statistically analysing the area data of fibres within the same category, the average cross-sectional area for that fibre type can be obtained. Meanwhile, the system automatically counts the number of fibres for each type to acquire the fibre count of different components. By combining the

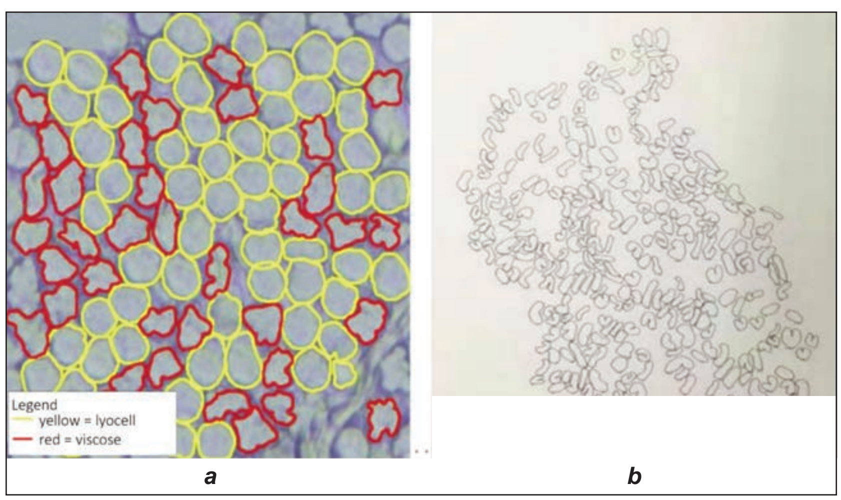

Fig. 7. Comparison of AI-automated and manually drawn cross-section effect diagrams: *a* – AI automatically generated cross-section effect diagram; *b* – traditional manually drawn cross-section effect diagram

Note: Comparison between AI-automated and manually drawn fibre cross-section contours on a cotton/regenerated-cellulose blended sample. a) AI result: contours produced by the AI system (U-Net segmentation with post-processing) and ready for area statistics: b) Manual result: technician-drawn contours of the same field. The AI workflow typically requires about 5 min per image versus ~60 min for manual drawing. Colours follow figure 5 (yellow = lyocell: red = viscose).

known density parameters of each fibre type, the mass percentage of cotton and regenerated cellulose fibres in the blended structure can be derived.

The blending ratio calculation formula used in this study is as follows:

$$P_{zi} = \frac{N_i \times S_i \times \rho_i}{\sum_{j=1}^{n} N_j \times S_j \times \rho_j} \times 100\% \qquad (1)$$

where P_{zi} is the mass percentage content of the *i*-th component fibre (%); N_i – the fibre count of the *i*-th fibre in the sample image; S_i – the average cross-sectional area of the *i*-th fibre (unit: μm^2); ρ_i – the material density of the *i*-th fibre (unit: g/cm^3); n – the total number of fibre types (in this study, it is 2, i.e., cotton and regenerated cellulose fibre).

This formula assumes that each fibre is a uniform cylinder, and the density of the same type of fibres is uniform and consistent. When the fibres are sectioned, their direction is perpendicular to the longitudinal direction of the fibres, and they are evenly spread on the slide, so the mass per unit length is directly proportional to the cross-sectional area. Therefore, under the condition of equal fibre lengths, the mass ratio can be estimated by the product of the cross-sectional area and density. This method is based on the premise that the thickness of the fibre sample slices is consistent and that the fibre sectioning is approximately perpendicular to the axis, making it applicable to most common cotton/regenerated fibre blended fabric cross-sectional image samples. Considering that in a single piece of fabric, there may be certain differences in the density uniformity of the same type of fibres, which leads to extremely small differences in the final calculated proportion of fibre components. Therefore, in the international market, a certain margin of error is allowed for the proportion of fibre components in fabrics. Within a certain range of error, the market and consumers are acceptable.

In practical applications, the research team conducts batch processing of cross-sectional images from different regions of the sample via glass slide scanning. For each image, the system automatically extracts the fibre count and cross-sectional area information for various fibre types, accumulating the results for blending ratio calculations using equation 1. The system supports batch fusion analysis of multiple images and can output detailed statistical reports for each fibre type as well as total blending ratio results.

Compared to traditional chemical dissolution methods, this image recognition-based computational approach has the following advantages:

- Non-destructive: it does not require chemical dissolution or physical destruction of the samples.
- High throughput: it supports high-resolution image batch processing analysis, offering high efficiency.
- Strong flexibility: it can adapt to various types of regenerated fibres and complex blended structures.
- Data traceability: each image segmentation, area, and ratio calculation can be visually annotated and traced.

According to experimental validation results, in 37 sets of cotton/regenerated fibre blended samples, the average error of the component content calculated by this method compared to the results from the chemical dissolution method is less than 3%, demonstrating good accuracy and practicality. This provides a reliable and efficient new pathway for subsequent textile component detection and quality control.

Accuracy verification and error analysis

To systematically verify the applicability and accuracy of the AI cross-sectional image recognition technology proposed in this study for cotton and regenerated cellulose fibre blended fabrics, this section employs a blind test method to conduct classification recognition and content determination experiments on multiple typical blended samples, comparing them with traditional manual recognition methods and standardised chemical dissolution methods.

A total of 37 batches of blended samples were collected for this experiment, covering three common types of regenerated cellulose categories: cotton/viscose, cotton/modal, and cotton/lyocell dual-component blended fabrics. Each sample was tested using the following three methods:

- Manual recognition method: based on experience, manually observing the cross-sectional microscopic images and estimating the component ratios.
- Chemical dissolution method: weighing the fibres after dissolution and separation according to standard methods (ISO 1833.6:2018).
- AI-based image analysis method: automatically segmenting contours based on the U-Net model, extracting areas, and deriving component percentages using the ratio calculation formula.

The results are shown in table 1, where the AI model's prediction results are highly consistent with those of the chemical dissolution method. The average error for the three blended categories is maintained within 3%, with some samples showing an error of less than 1%. The maximum absolute deviation does not exceed 2.7%, meeting the industry requirements for error range as specified by the ISO 1833.6:2018 standard. Meanwhile, the AI method demonstrates a significant advantage in testing efficiency, reducing the average detection time per sample from 60 minutes for manual operation to less than 5 minutes, resulting in an approximately 12-fold increase in testing efficiency, with no consistency bias among testers, thus exhibiting higher repeatability and automation potential. However, the required equipment and consumables remain unchanged, and the professional technical ability requirements for operators have been reduced. At the same time, manual operation is eliminated, which will also greatly reduce the harm to operators inhaling the smell of chemicals for a long time.

Table 1

COMPARISON OF COMPONENT CONTENT MEASUREMENT RESULTS AND MAXIMUM ERRORS FOR TYPICAL BLENDED SAMPLES USING DIFFERENT METHODS

Sample composition	Sample number	Traditional manual methods		Chemical dissolution method		AI-based detection method		Maximum change (%)
		Fibre 1 content (%)	Fibre 2 content (%)	Fibre 1 content (%)	Fibre 2 content (%)	Fibre 1 content (%)	Fibre 2 content (%)	
Cotton/ Viscose fibre	1	61.3	38.7	60.0	40.0	62.4	37.6	2.4
	2	50.8	49.2	50.5	49.5	50.6	49.4	0.2
	3	53.5	46.5	53.0	47.0	55.4	44.6	2.4
	4	42.7	57.3	45.0	55.0	43.0	57.0	2.0
	5	51.8	48.2	52.5	47.5	53.1	46.9	1.3
	6	73.2	26.8	71.8	28.2	72.4	27.6	0.8
	7	64.7	35.3	64.6	35.4	63.8	36.2	1.1
	8	64.0	36.0	62.5	37.5	62.9	37.1	1.1
	9	47.8	52.2	49.4	50.6	49.9	50.1	2.1
	10	50.2	49.8	50.1	49.9	51.4	48.6	1.2
	11	68.5	31.5	70.0	30.0	70.0	30.0	1.5
	12	69.8	30.2	71.5	28.5	70.1	30.0	1.4
	13	38.6	61.4	40.0	60.0	39.6	60.4	1.0
Cotton/ modal fibre	14	48.8	51.2	47.1	53.0	46.1	53.9	2.7
	15	67.5	32.5	68.5	31.5	69.6	30.4	2.1
	16	61.2	38.8	60.0	40.0	60.8	39.2	0.8
	17	67.2	32.8	66.9	33.1	65.4	34.6	1.8
	18	28.1	71.9	27.5	72.5	26.7	73.4	1.4
	19	72.4	27.6	70.2	29.8	71.7	28.3	1.5
	20	71.7	28.3	70.5	29.5	71.2	28.8	0.7
	21	13.5	86.8	13.0	87.0	11.7	88.3	1.8
	22	27.7	72.3	28.5	71.5	26.7	73.4	1.8
	23	36.2	63.8	36.8	63.2	35.8	64.3	1.0
	24	81.3	18.7	80.2	19.8	79.0	21.0	2.3
	25	55.8	44.2	55.0	45.0	54.0	46.0	1.8
	26	52.6	47.4	51.5	48.5	52.6	47.4	1.1
Cotton/ Lyocell fibre	27	50.2	49.8	49.8	50.2	49.3	50.7	0.9
	28	54.0	46.0	56.0	44.0	54.4	45.6	1.6
	29	82.5	17.5	82.4	17.6	83.4	16.6	1.0
	30	86.9	13.1	88.6	11.4	87.1	12.9	1.5
	31	82.0	18.1	80.6	19.4	82.3	17.7	1.7
	32	72.0	28.0	70.5	29.5	71.8	28.2	1.3
	33	36.5	63.5	37.6	62.4	36.2	63.8	1.4
	34	37.5	62.5	40.2	59.8	39.3	60.7	1.8
	35	51.3	48.7	50.7	49.3	49.2	50.8	2.1
	36	48.0	52.0	50.6	49.4	49.0	51.0	1.6
	37	50.2	49.8	50.0	50.0	51.0	49.0	1.0

Note: Fibre 1 refers to cotton, and Fibre 2 refers to the corresponding regenerated cellulose fibre.

Additionally, in different blended combinations, the AI model shows slightly higher accuracy when identifying regular morphologies (such as lyocell). However, in handling cotton/viscose samples with similar morphologies, some samples exhibit an error of about 2%. This is primarily limited by boundary overlap and local cross-section blurriness, which leads to area error propagation. In addition, focusing deviation during image acquisition can lead to blurred imaging, fibre slicing is not completely kept perpendicular to the longitudinal direction, and damage to the fibre cross-section can cause semantic analysis defects, all of which may affect the calculation of the fibre cross-sectional area and thereby cause errors in the final model test results. Future improvements can be made by enhancing the optical image resolution, optimising segmentation details, and introducing density adjustment coefficients to continuously improve recognition accuracy.

Therefore, the AI cross-sectional automatic recognition method proposed in this study demonstrates good accuracy in determining blending ratios, with significantly shorter testing times compared to traditional methods. It also exhibits high stability and repeatability, making it suitable for high-throughput rapid detection of industrial bulk samples. This provides a practical and feasible intelligent solution for fibre component analysis and quality control.

Failure cases and edge scenarios

To present the method's boundaries, this study includes four representative cases (figure 8).

Case *a* (figure 8, *a*, over-thick & laid-down/tilted, ex. 1): cross-sections become elongated with chromatic halos; foreground bridging causes merged adjacent sections, biasing areas upward and shifting composition estimates. Case *b* (figure 8, *b*, over-thick & laid-down/tilted, ex. 2): local defocus and banding suppress weak edges; slender bands are over-connected into clusters. Case *c* (figure 8, *c*, over-thin): low contrast weakens fibre-wall signals; broken/fragmented contours underestimate areas or remove small sections. Case *d* (figure 8, *d*, bubble-rich field): Numerous circular bubbles and refractive halos introduce large dark blobs and spurious edges whose size/shape differ from true cross-sections, leading to segmentation failure or unreliable type recognition.

Each subfigure shows a raw image, ground-truth/predicted mask, and human-corrected outline.

Mitigations: 1) Thickness/pose QC with Laplacian variance – and edge-width – thresholds and automatic rescanning; 2) focal stacking for sharper edges; 3) post-processing with minimum component area, closing, and hole-filling; 4) bubble detection

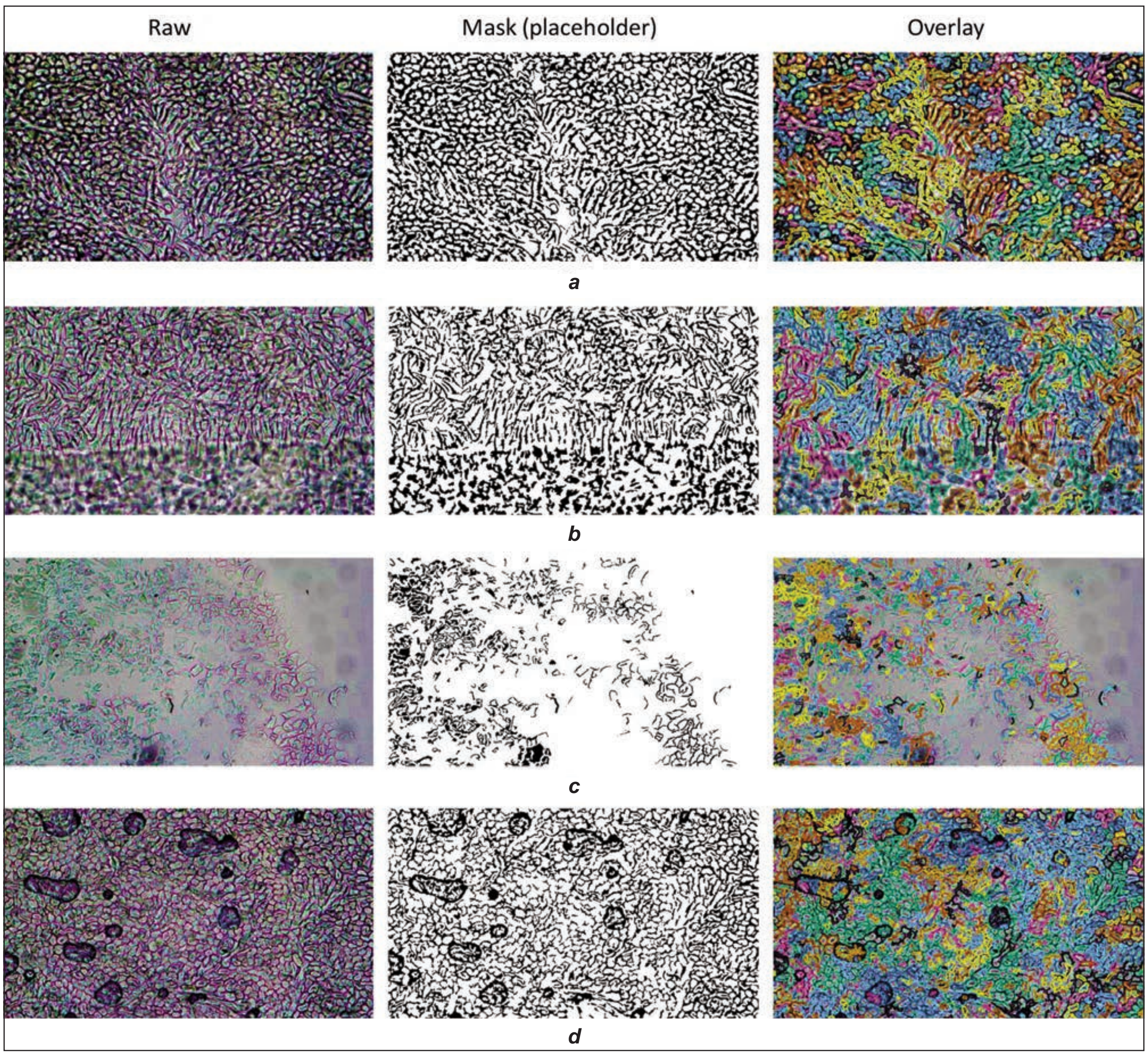

Fig. 8. Representative failure/edge scenarios: *a* and *b* – over-thick, laid-down/tilted slices (two examples): strong halos and banding lead to bridging/merging of adjacent sections; *c* – over-thin slice: low contrast breaks contours, causing fragmentation and area under-estimation; *d* – bubble-rich field: numerous bubbles and refractive halos create spurious edges and large connected components, breaking segmentation and fibre-type recognition

and masking using circularity/diameter/gradient cues; 5) ±Δ sensitivity analysis on density and threshold parameters with confidence intervals. These measures substantially reduce errors in problematic fields.

EXPERIMENTAL DESIGN AND DATA ANALYSIS

Experimental samples and operating procedures

To verify the applicability and accuracy of the AI image segmentation method for cotton and regenerated cellulose blended fibres, this study established a standardised experimental process, including sample selection, section preparation, image acquisition, model recognition, and ratio calculation. The specific operational steps are presented in the following subsections.

Source and categories of experimental samples

This study tested a total of 37 batches of blended samples, covering three typical dual-component combinations, as detailed below:

- Cotton/Viscose fibres: 13 batches;
- Cotton/Modal fibres: 13 batches;
- Cotton/Lyocell fibres: 11 bat0ches.

A cooperating laboratory provided all samples with testing qualifications, and the original blending ratios are known, covering a range of component ratios from 30% to 80%, making them highly representative and generalizable. Some physical samples are displayed in figure 9.

Preparation of cross-sectional slices

The following standardised slicing steps were used to prepare fibre cross-section observation slides:

- use resin embedding material for vacuum impregnation and shaping of the samples;
- employ a precision microtome to cut along the vertical direction with a thickness controlled between 10–15 μm;
- after pre-drying, impurity removal, and drying treatment, standard slices suitable for microscopic observation are obtained.

All samples are processed under the same batch conditions to ensure thickness consistency and microscopic imaging contrast.

Microscopic image acquisition and calibration

Using a self-developed image acquisition platform (as detailed in the 2nd section), high-definition cross-sectional images are captured at a magnification of 200× – 400×. For each sample area, at least 10 images are collected, and, through pixel-size calibration, the images are converted to a μm^2 scale. The collected images undergo preliminary quality screening before being used for AI model analysis.

For each field, this study computes Laplacian variance S and an edge-width metric W as proxies for imaging/thickness; frames with $S < S_{min}$ or $W > W_{max}$ are flagged as over-thin/over-thick or defocused and rescanned. This study also detects bubble-rich fields using circularity/diameter and local-contrast heuristics and either masks the affected regions or triggers rescanning. This study performs ±Δ sensitivity analysis on the binarisation threshold and density parameters and reports confidence intervals of composition changes.

An AI model for automatic recognition and segmentation

The collected images are input into the fully trained U-Net deep learning model, which automatically performs the following operations:

- conduct pixel-level semantic segmentation of all cross-sectional fibres in the image;
- output category label mask images and individual contour data;
- automatically identify fibre types (Cotton/Regenerated Cellulose) and perform quantity statistics.

After the segmentation results are exported, they enter the post-processing module for area calculation and contour visualisation.

Blending ratio calculation and output

The system calculates the blending ratio based on the mass percentage formula provided in equation 1. The parameters for each fibre type are derived from the area, fibre count, and standard density data extracted from the images.

Verification and error validation

To ensure model stability and result reliability:

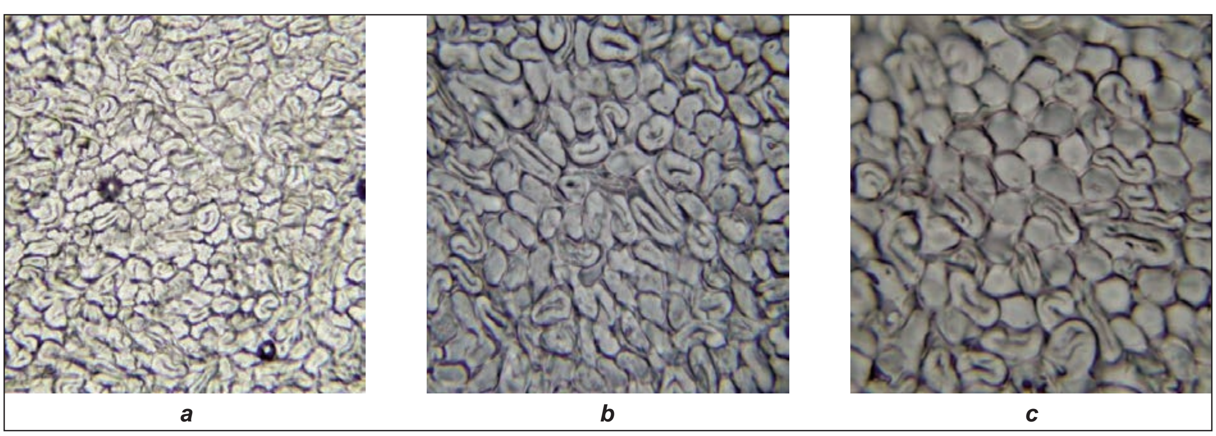

Fig. 9. Physical image of cotton and regenerated cellulose blended fibre samples for experiment:
a – Cotton/viscose fibre; *b* – Cotton/modal fibre; *c* – Cotton/lyocell fibre

- randomly sample 10% of the image results for each type of sample, and have an expert manually review the contour and classification accuracy;
- compare the AI results with the chemical dissolution method, calculating the absolute error as a standard for system performance evaluation.

Use statistical indicators such as standard deviation and maximum deviation to analyse the robustness of the methods.

Summary and discussion of experimental data

To comprehensively assess the practical performance of the AI cross-sectional analysis method based on the U-Net model in identifying blended fabric components, the research team conducted experimental determinations and comparative analyses on 37 batches of cotton/regenerated cellulose blended samples. The samples covered three typical blended combinations: cotton/viscose, cotton/modal, and cotton/lyocell. The measured results were obtained using manual interpretation, standardised chemical dissolution methods, and AI recognition methods, with a systematic comparison focusing on accuracy, efficiency, and stability.

From an overall accuracy perspective, the performance of the AI method is highly consistent with the chemical dissolution method. The average absolute error for the detection results of the three types of blended samples is 1.42%, with a maximum deviation not exceeding 2.7%. Among them, the recognition accuracy for the cotton/lyocell group is the highest, with an average error of only 1.31%. This trend is closely related to the geometric morphology of the fibre cross-sections: Lyocell fibres have regular cross-sections and clear boundaries, which facilitate accurate segmentation by the model; whereas cotton and viscose have more similar cross-sectional morphologies and grayscale distributions, which can lead to some misidentifications, resulting in slightly higher errors. Overall, the AI model demonstrates strong adaptability and robustness across all three combinations.

To visually represent the error differences among the three typical blended combinations, figure 10 illustrates the maximum error bar chart for six representative samples between the AI detection method and the chemical dissolution method. The results indicate that the AI method exhibits higher consistency in the cotton/lyocell samples, while some samples in the cotton/viscose combination show slightly higher errors but remain within an acceptable range. This reflects the AI model's stronger segmentation adaptability for fibre morphologies with clearer cross-sections.

Further analysis reveals that the errors in some samples primarily stem from fluctuations in image quality, deviations in fibre cutting angles, and assumptions regarding the use of standard density parameters. For instance, issues such as fibre stacking, uneven dyeing, and local blurriness in certain areas may lead to slight deviations in the segmentation model's judgment of boundaries, thereby affecting the accuracy of area extraction. Additionally, in the experiments, all fibre components were calculated using a uniform density value, neglecting microscopic density fluctuations caused by different sources of raw materials, which may result in slight deviations in the calculations for edge samples. Nevertheless, these errors are controlled within 2%, sufficiently meeting the accuracy requirements of current industry standards.

To verify the stability of the AI detection method, 10 samples were randomly selected from 37 samples, and each sample was tested 10 times. The experimental results showed that the maximum standard deviation of the 10 samples was 0.028 and the minimum was 0.011, indicating that this method has good reliability and repeatability.

Apart from accuracy performance, the advantages of the AI detection method in testing efficiency are particularly significant. Traditional manual methods typically require 60 minutes to complete the identification and mapping of a single sample, while the AI method can output component ratios and statistical results in just about 5 minutes under standard image input conditions, achieving an efficiency increase of over 10 times. More importantly, this method does not require any chemical dissolution processes, making it non-destructive and environmentally friendly, particularly suitable for large-scale testing scenarios and subsequent quality traceability needs.

Combining experimental results with system performance, it is evident

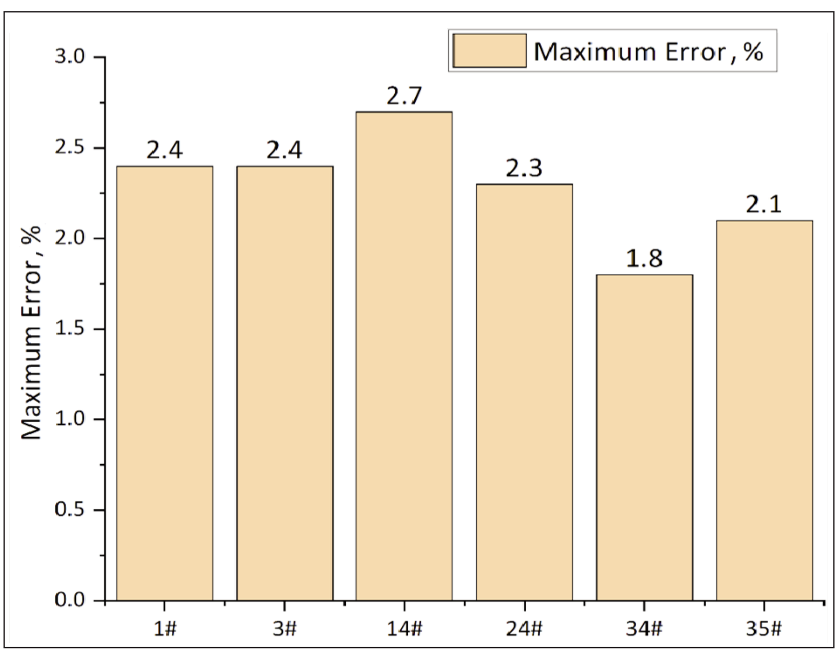

Fig. 10. Comparison bar chart of maximum errors between the AI detection method and the chemical method for different typical blended samples

that the U-Net model-based cross-sectional image recognition method not only possesses good quantitative analysis capabilities but also maintains stable output under different fibre types, blending ratios, and imaging conditions. Compared to traditional methods, it exhibits significant advantages in accuracy, efficiency, and operational safety. In the future, this method is expected to be extended to more complex three-component or functional fibre blended systems, while optimising model parameters through big data training to further enhance classification accuracy and application breadth.

CONCLUSION AND OUTLOOK

This study addresses the challenge of detecting fibre components in cotton and regenerated cellulose blended fabrics that are difficult to separate chemically, proposing an AI cross-sectional quantitative recognition method that integrates high-resolution microscopic image acquisition, deep learning segmentation models, and structural contour analysis. This method centres on the U-Net architecture and combines multi-image fusion strategies and contour vector reconstruction techniques to achieve automatic recognition of fibre cross-section structures, area extraction, and blending ratio derivation, establishing an intelligent pathway from “image perception” to “quantitative analysis”.

In terms of the image acquisition system, this paper constructs a multi-modal microscopic imaging platform that integrates VCM focusing, high-precision moving platforms, and 3D composite optical paths, significantly enhancing the stability, depth, and contrast of high-magnification images, ensuring the quality and stability of the input data for the AI model. In the image analysis phase, the U-Net model was trained on over 100,000 sample images and optimised through expert review, ultimately achieving high-precision segmentation and recognition in typical cotton/regenerated cellulose blended fabrics. Experimental results indicate that this method achieves an average absolute error of 1.42% across 37 test samples, with a maximum deviation not exceeding 2.7%. This performance surpasses the consistency of manual methods and maintains high agreement with standardised chemical dissolution methods. Meanwhile, detection efficiency has improved to one-tenth of the original, demonstrating strong potential for engineering applications.

The AI cross-sectional analysis method proposed in this paper retains core advantages of being non-destructive, rapid, and automated while fully adapting to the differences in fibre microstructures. It provides a new pathway for addressing the issues of traditional methods in handling complex fibre systems, such as poor timeliness, high environmental burden, and strong subjectivity. It has good expansion value in standardising detection, smart production, textile quality control, and traceability system construction.

This study additionally reports four failure/edge cases (two over-thick laid-down/tilted, one over-thin, and one bubble-rich field) with targeted QC and post-processing strategies, delineating the method’s applicability under non-ideal slicing.

Future research can further optimize and expand in the following directions: (1) constructing a multi-channel segmentation network with stronger generalization capabilities for three-component and functional fibre blended structures; (2) introducing spatial attention mechanisms or Transformer architectures to enhance the model’s sensitivity to low-contrast areas; (3) establishing a dynamic weighting system in conjunction with a density database to further improve the true accuracy of ratio calculations; (4) integrating this system into a real-time detection platform on production lines to achieve closed-loop control of fibre component analysis throughout the entire process. Through bidirectional iteration of technology and application, this method is expected to become a core foundational tool for fibre identification and blending analysis in the future textile industry.

ACKNOLEDGEMENTS

The authors would like to thank the technical teams from United Testing Services (Foshan) Co., Ltd. and United Testing Services (Jiangxi) Co., Ltd. for their valuable support in sample preparation and image acquisition. Special appreciation is extended to the Jiangxi Centre for Modern Apparel Engineering and Technology for their assistance in data annotation and model validation. This paper was financially supported by the Science and Technology Research Project of the Jiangxi Provincial Department of Education, titled “R&D and Innovation in Textile Product Testing Technologies” (CN) (GJJ250XXXX). This paper was financially supported by the United Testing Services (Jiangxi) Co., Ltd. project titled “R&D and Innovation Support for Textile Product Testing” (CN) (JFHX202521). This paper was financially supported by the China National Textile and Apparel Council Scientific Guidance Project (CN) (2019111). This paper was financially supported by the Research Project of United Testing Services (Foshan) Co., Ltd. (CN) (RD2518).

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