A Modular Deep Learning Pipeline (CNN+U-Net+GAN) for Color-Accurate, Cross-Material Digital Textile Printing with Transfer-Learning-Based Material Adaptation

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Keywords: digital printing, pattern creation, color restoration, material compatibility

Received: August 27, 2025

Precise color reproduction and efficient pattern generation are the core goals of digital printing on clothing. To break through the limitations of traditional processes that rely on manual parameter adjustment and sample fabric trial and error, this paper proposes an intelligent printing generation framework based on deep learning. This framework integrates CNN color management, deep segmentation and loop optimization, GAN-driven 3D virtual rendering and transfer learning material adaptation, and can achieve end-to-end pattern generation and computational optimization on multi-material data such as cotton fabric, silk and polyester. The system not only captures the spatial detail features of the patterns (such as edge sharpness and color gradation), but also maintains color consistency and detail restoration among different materials through cross-domain modeling. The experimental results show that on multi-material datasets, this scheme achieves ΔE 1.9±0.2across cotton/silk/polyester (mean over 3 runs), which corresponds to a 30–45% reduction versus screen printing (ΔE≈4.1) and 15–25% versus a commercial inkjet baseline (ΔE≈2.3). It reduces splicing fracture rate to <4%, shortens average processing time by ~60% (12 h→4.8–8.5 h depending on batch size), and increases SSIM to 0.93±0.01.All statistics are mean±std over three independent runs; significance is assessed with paired t-tests or ANOVA with Bonferroni correction at α=0.05. This research not only verified the effectiveness of deep learning in digital printing, but also provided an expandable intelligent path for the integration of the clothing design and production chain, offering significant support for the transformation of the fashion industry towards personalization, greenness and intelligence.

Povzetek: Članek predstavi modularni sistem (CNN + U-Net + GAN) za barvno natančno, večmaterialno digitalno tiskanje tekstila. Z globokim učenjem, cikličnim spajanjem in prenosnim učenjem doseže odlične razultate.

1 Introduction

Unlike traditional processes that rely on manual design and experience-based adjustment, digital printing based on deep learning can achieve automatic pattern generation, style transfer, and multi-material adaptation through convolutional neural networks (CNNs), generative adversarial networks (GANs), and image-to-image conversion frameworks such as Pix2Pix and CycleGAN. It enables clothing design to possess unprecedented flexibility and precision in terms of color expression, texture details and structural restoration.

In response to the above issues, this paper proposes a deep learning-driven intelligent generation and computing implementation framework for digital printing patterns on clothing, and conducts research from four dimensions: Color restoration and management based on CNN, pattern segmentation and cyclic optimization based on deep segmentation networks, virtual rendering and 3D proofing combined with GAN, resolution control and material adaptation based on cross-domain transfer learning. Through this holistic approach, it is expected to break through the problems of lagging feedback in traditional craftsmanship, large deviations between design and finished products, and frequent manual corrections, achieving efficient, automated and intelligent pattern generation, and providing strong support for the development of the fashion industry towards green and personalized directions.

The remaining structure of this article is arranged as follows: The second part reviews the research progress of deep learning and digital printing. The third part elaborates on the proposed intelligent generation framework and key computing mechanisms. The fourth part demonstrates the performance of this method in pattern generation and effect optimization in combination with experimental data. The fifth part discusses and analyzes its industrial application value. The sixth part summarizes the research conclusions and looks forward to the future development direction.

2 Related work

Although digital printing shows broad application prospects in clothing design, it still faces complex challenges in the intelligent generation of patterns [5]. Firstly, the issue of color reproduction has long plagued the connection between design and production. There is often a difference between the effect on the screen and the actual presentation on the fabric, especially during high saturation and gradient transitions, when deviations are more likely to occur. Secondly, during the process of splicing and circular design of large-scale patterns, edge breaks or repetitive marks often occur, which weakens the consistency of the overall aesthetic [6]. Furthermore, the differences in droplet diffusion and penetration performance among various fiber materials make it difficult to unify resolution control and detail restoration. Therefore, it is urgent to explore an intelligent path that can integrate deep learning models with multi-dimensional process parameters to promote the transformation of digital printing on clothing from "numerical control" to "intelligent generation" [7].

In the early stage of development, related research mostly focused on empirical and statistical methods, such as establishing fundamental rules based on color physical tests or fiber adsorption experiments [8]. However, these methods have insufficient adaptability in complex patterns and cross-material environments and can only achieve local optimization. With the emergence of computer-aided design and virtual simulation tools, pattern layout and loop design have gradually entered the digital stage. The parametric pattern-making method enables custom clothing to have flexible pattern generation and size adaptation capabilities, while computational geometry and CAD algorithms promote the automatic transformation from three-dimensional clothing models to two-dimensional cutting pieces, thereby achieving efficient connection between pattern design and structural design [9].

In recent years, the introduction of deep learning technology has become a breakthrough. On the one hand, the color prediction model based on convolutional neural Network (CNN) and Residual network (ResNet) can learn the nonlinear response laws of fiber materials, thereby significantly reducing ΔE color difference. On the other hand, generative adversarial networks (GANs) and image-to-image transformation frameworks (such as Pix2Pix and CycleGAN) have been applied to intelligent pattern generation and style transfer, achieving color enhancement and texture expansion while maintaining the original structure. Three-dimensional virtual simulation is gradually integrating with deep learning. For instance, it can automatically locate pattern regions through image segmentation networks and then map them onto three-dimensional clothing grids for realistic rendering, thereby achieving dynamic visualization effects in the design stage [10]. These studies have jointly driven the transformation of clothing patterns from "handcrafted creation" to "intelligent synthesis", but there are still problems such as high computational overhead, insufficient cross-material generalization ability, and complex realistic rendering.Compared with prior studies that focus on single-material color prediction or creative synthesis, our framework jointly optimizes color mapping, segmentation/loop tiling, and 3D rendering within one learning pipeline, and further introduces transfer learning for cross-material adaptation. Specifically, beyond Pix2Pix-based silk color prediction [17] and generic generative design models [18], we explicitly model fabric features and seam continuity, reducing ΔE across cotton/silk/polyester to 1.9±0.2 and the splicing fracture rate (SFR) to 3.8%±0.9%, while increasing SSIM to 0.93±0.01. Unlike CAD-oriented geometric pipelines for 3D-to-2D panel conversion [15] and process-level method comparisons across printing technologies [10], our system provides end-to-end, statistically validated gains on real prints under matched RIP and pre-treatment settings. In short, our contribution lies in unifying color management, structural tiling, and material adaptation—dimensions that prior work typically treats in isolation.

To systematically present the existing research achievements, Table 1 summarizes the typical studies in digital printing and deep learning-driven intelligent generation in recent years, covering the models used, application scenarios, main evaluation indicators and their limitations.

Table 1: A Comparison of typical Studies on digital Printing in pattern Creation

Author (Year)	Method / Technique	Application Scenario	Key Metrics	Limitations
Gill (2024) [2]	Digital Parametric Pattern Making	Customized Garment Pattern Generation	Precision, Consistency	Limited adaptability to complex materials
Pietroni (2022) [15]	Computational Geometry + CAD	3D-to-2D Garment Panel Conversion	Automation Efficiency	Errors with complex surfaces
Choi (2022) [8]	3D Virtual Fitting System	Dynamic Try-on & Pattern Visualization	Visual Realism	High rendering cost
Li Y (2023) [16]	Pigment-based Color Modeling	High-Precision Color Control in Printing	ΔE, Stability	Limited support for complex patterns
Zhu (2023) [17]	Pix2Pix Deep Learning Framework	Silk Pattern Color Prediction	Color Reproduction Accuracy	Requires large-scale training samples
Wu (2024) [18]	Generative Deep Learning Model	Creative Pattern Design	Diversity, Creativity	High computation and training costs
Glogar (2024) [19]	Eco-friendly Preprocessing + Printing	Sustainable Pattern Production	Durability, Eco-friendliness	Relatively high process cost
Walker (2024) [10]	Sublimation, DTG, Screen Printing Comparison	Brand Pattern Quality Assessment	Durability, Color Stability	High equipment demand, no unified standard

Based on the above gaps, this paper raises the following research questions:

(1) Can a unified deep learning framework be established to jointly optimize color management, pattern segmentation, virtual rendering and material adaptation, so as to enhance the stability and accuracy of pattern generation?

(2) How can convolutional neural networks (CNNs), generative Adversarial networks (GANs), and attention mechanisms be utilized to dynamically optimize recurrent units and large-scale splicing, avoiding breakage and repetitive traces?

(3) In a multi-material environment, can color and detail consistency among different fabrics be achieved through transfer learning and cross-domain feature mapping?

The main contributions of this article include:

A multi-dimensional intelligent generation solution framework has been constructed, covering key links such as color management based on deep learning, pattern segmentation and layout optimization, virtual rendering and 3D proofing, resolution control and material matching, providing systematic support for digital printing on clothing.

An optimization mechanism combining deep segmentation networks and geometric concatenation is proposed, and a visual continuity loss function is introduced to effectively enhance the integrity and naturalness of large-area designs.

Integrating generative adversarial networks and fabric physical modeling in the virtual rendering process enhances the mapping efficiency between the design end and the finished product end, enabling designers to quickly identify potential problems in the early stage of creation.

The linkage adjustment mechanism between resolution control and material adaptation was verified through cross-material dataset experiments. The results show that among the three types of materials, namely cotton, silk and polyester, the average color difference ΔE is reduced to below 2.0, significantly improving the detail representation and color reproduction.

The performance of the proposed deep learning framework in terms of accuracy, efficiency and cross-material adaptability was systematically evaluated. The results showed that it outperformed traditional solutions and existing commercial systems in both objective indicators and subjective aesthetic feedback.

3 Suggested solutions

In the intelligent generation framework proposed in this paper, the combination path of "color management and restoration based on CNN - pattern segmentation and loop optimization based on deep segmentation network - virtual rendering and 3D proofing combined with GAN - resolution control and material adaptation based on transfer learning" is chosen, considering their complementary advantages in dealing with the challenges of generating complex clothing patterns.For reproducibility, we provide complete model specifications, loss compositions, training schedules, and hardware details for each module, including layer-by-layer architectures, hyperparameters, and random seeds.

In the color management and restoration module, the introduction of convolutional neural network (CNN) and residual learning mechanism can achieve nonlinear color mapping under cross-device and cross-material conditions, significantly reducing the ΔE color difference between the design end and the finished product end. Compared with the traditional scheme that only relies on ICC curves, this method can capture material features through end-to-end training and quickly complete color correction in the reasoning stage, ensuring the color consistency of different fabrics.

In the pattern segmentation and cyclic optimization stage, traditional geometric algorithms have difficulty handling the boundary continuity problem of large-format patterns. In this paper, deep segmentation networks (such as U-Net and DeepLabV3+) are adopted to extract the boundaries of recurrent units, and combined with the attention mechanism to achieve high-precision splicing of key regions. By minimizing perceptual loss and gradient continuity constraints, the network can automatically optimize the cyclic layout of large-area patterns, thereby reducing breaks and repetitive traces.

In the virtual rendering and 3D proofing stages, this paper introduces a method that combines generative adversarial networks (GAN) with physically-driven fabric modeling. GAN is responsible for enhancing texture details and lighting effects during the 3D mesh mapping process, while fabric simulation based on the mass-spring model ensures the physical authenticity of wrinkles, stretches and drape. This method not only enhances the visual fidelity of the patterns but also provides designers with a real-time interactive virtual sample-making platform, significantly shortening the creation-production chain.

In terms of resolution control and material adaptation, this paper adopts transfer learning and cross-domain feature mapping techniques to establish a unified high-resolution generative model for multiple materials. By sharing convolutional features between the source domain (such as the cotton fabric dataset) and the target domain (such as the silk and polyester datasets), the model can automatically adjust the jetting parameters and detail representation while maintaining the clarity of the pattern, achieving consistent output across materials. This mechanism effectively resolves the issue of inconsistent resolution caused by the differences in ink droplet diffusion and adsorption among various fiber materials.

Compared with the schemes that solely rely on color calibration or only use 3D proofing, the overall framework proposed in this paper can solve the pain points of multiple links in parallel with the support of deep learning, avoiding the limitations of "local optimization". Through the collaboration and information sharing among modules, the system not only enhances the accuracy and robustness of pattern generation, but also possesses the capabilities of cross-platform expansion and rapid iteration.

Figure 1 shows the overall architecture of the proposed intelligent generation of digital printing on clothing based on deep learning. This architecture processes the input design patterns in sequence through four core modules:

Firstly, color management and restoration based on CNN to achieve consistency across materials; Then comes the deep segmentation and loop optimization module, ensuring the continuity of large-format patterns; Next comes the combination of GAN's virtual rendering and 3D proofing, providing visual preview and interactive feedback; The last one is the transfer learning-driven resolution and material adaptation module, which ensures that the output maintains high fidelity and detail integrity on different fabrics.

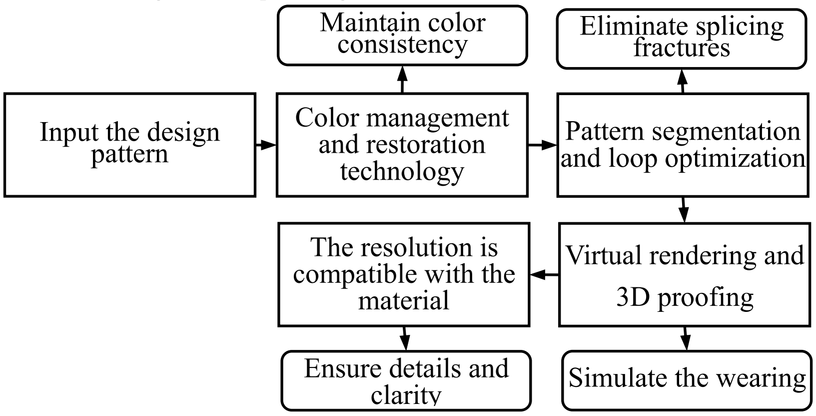

Figure 1: Framework of the solution for digital printing in the creation of clothing patterns

3.1 Color management and restoration technology based on deep learning

In the intelligent pattern generation process of digital printing, the precise management and restoration of colors are the key links to ensure that the design intention is consistent with the final product effect. Due to the significant differences between the screen end and the fabric end in terms of display medium, optical properties, and material adsorption, cross-device mapping relying solely on ICC Profile often fails to meet the requirements. Therefore, this paper introduces a deep learning-driven color prediction model. We use a 12-layer CNN (Conv-BN-ReLU blocks) with a residual backbone: Conv(3×3,64)→Conv(3×3,64)→MaxPool→Conv(3×3,128)→Conv(3×3,128)→MaxPool→ResBlock(128)×2→Conv(3×3,256)→GlobalAvgPool→FC(256→64)→FC(64→4 for CMYK). Material features S (surface roughness, absorption rate, whiteness) are injected via FiLM conditioning at the 3rd and 5th convolutional blocks.

Firstly, the traditional method establishes a standardized ICC file, and maps the RGB source space to the CMYK or extended color space through the color conversion matrix M:

$$C_{out}=M \cdot C_{in}, M\in \mathbb{M}^{4\times3} \quad (1)$$

Among them, C_{in} is the RGB vector at the input end, C_{out} is the CMYK vector at the print end, and the matrix M is obtained from the device characteristic curve and experimental calibration.

However, traditional linear mapping is difficult to characterize the nonlinear response under complex materials. This paper adopts a convolutional neural network (CNN) to construct a nonlinear color prediction model:

$$\hat{C}_{out}=f_\theta(C_{in},S) \quad (2)$$

Among them, f_θ represents the CNN model, and the parameter θ is obtained through training. The input includes the pixel value C_{in} at the design end and the material feature S (such as surface roughness, ink absorption rate), and the output is the optimized CMYK color vector.

During the optimization process, the CIE 1976 ΔE*ab color difference is taken as the loss function:

$$\Delta E_{76}=\sqrt{(L^*-L_T^*)^2+(a^*-a_T^*)^2+(b^*-b_T^*)^2} \quad (3)$$

Here, L^*、a^*、b^* denote the luminance, red–green axis and yellow–blue axis coordinates of the predicted output, while L_T^*、a_T^*、b_T^* represent the corresponding reference values of the target design. To further enhance the generalization ability across materials, this paper introduces a transfer learning strategy in training: first, a benchmark model is trained on cotton fabric samples, and then fine-tuned with a small amount of silk and polyester data, thereby achieving consistent prediction across materials. Experiments show that this method can keep ΔE below 2.0 and improve the color reproduction accuracy by approximately 30% compared with the traditional ICC + LUT correction. Before each session a one-point and multi-point spectral calibration is executed; drift is monitored by re-measuring a three-level gray ramp at the start and end of the run and remained within $\Delta E_{ab}^*<0.3$.

In practical implementation, the color management system in this paper consists of three steps: ①Using a spectrophotometer to collect training samples and construct material feature vectors; ②Nonlinear color mapping and prediction output are completed through the CNN model; ③In the production process, closed-loop feedback is introduced to feed back the measured ΔE index to the model for parameter update, thereby achieving continuous optimization.Unless stated otherwise, color difference is computed as CIE 1976 ΔE_{ab}^* from five repeated measurements per patch (rotated by 90° between readings) and then averaged; instrument repeatability is verified daily with a white ceramic standard.Training details: Adam optimizer (β1=0.9, β2=0.999), initial LR=1e−3 with cosine decay to 1e−5, batch size=16, epochs=120, early stopping patience=15, weight decay=1e−4, random seed=2024. Data augmentation: random rotation ±15°, scale 0.9–1.1, horizontal/vertical flip p=0.5, color jitter (brightness/contrast/saturation ±10%). Transfer learning: pretrain on cotton, then fine-tune last 4 layers + FiLM parameters using 20 silk and 20 polyester samples per epoch (freeze lower layers).

3.2 Pattern segmentation, layout and loop unit optimization techniques

In the digital printing process of clothing patterns, segmentation and layout are the key links to efficiently transform design patterns into producible units. Traditional printing often relies on manual splicing or repetitive units, which can easily lead to uneven edges, broken splicing or overly obvious repetitive marks. To this end, it is necessary to introduce digital segmentation and cyclic optimization mechanisms to achieve the continuity and integrity of patterns on large areas of fabric.

Firstly, pattern segmentation is usually based on geometric matrix partitioning and edge detection techniques. Let the original pattern be a two-dimensional pixel matrix I(x,y), and it is divided into several basic regions through the boundary extraction function B(x,y) :

$$B(x,y)=\begin{cases}1, if\ I(x,y)\in \Omega_{pattern}\\ 0, if\ I(x,y)\in \Omega_{background}\end{cases} \quad (4)$$

Among them, $\Omega_{pattern}$ represents the pattern area and $\Omega_{background}$ represents the background area. Different from traditional edge detection, we adopt U-Net (encoder: ResNet34; decoder: bilinear upsampling + skip connections) with attention gates (channel + spatial SE blocks) to focus on high-frequency edges and extract repeat-unit boundaries. Input size is 1024×1024; loss is Dice+Focal (α=0.25, γ=2.0).

During the layout stage, it is necessary to perform translation and rotation operations on the segmented units to ensure that the repeated units are seamlessly connected on the two-dimensional plane. Common splicing methods include right-angle translation, mirror splicing and hexagonal tiling. Its mathematical expression can be achieved through the translation matrix:

$$T=\begin{bmatrix}1 & 0 & m\\ 0 & 1 & n\\ 0 & 0 & 1\end{bmatrix} \quad (5)$$

Among them, m and n respectively represent the lateral and vertical translation distances. By constraining the gradient continuity of color and texture at the loop boundary, the visual discomfort caused by splicing breakage can be effectively reduced. Introducing an energy minimization model is an effective approach in the optimization of cyclic units. The pixel differences at the unit edges are constrained by constructing the boundary energy function E:

$$E\sum_{i=1}^{N}\| I(x_i,y_i)\text{-}I(x_i+m,y_i+n)\|^2 \quad (6)$$

Here, (x_i,y_i) represents the coordinates of the boundary pixels. The process of minimizing E is actually to find the best cyclic unit so that the spliced area is highly consistent in color and texture. Meanwhile, in modern digital systems, this paper combines Poisson Blending and Deep Generative Network (GAN) for transition processing to further improve the naturalness after splicing. We formally define the splicing fracture rate (SFR) as the percentage of seam pixels whose gradient-magnitude mismatch across the seam exceeds a tolerance τ:

$$SFR=\frac{1}{|\Gamma|}\sum_{p\in\Gamma} I(\|\nabla T_L(p)-\nabla T_R(p)\|_2>\tau)\times 100\% \quad (7)$$

where denotes all pixels along the seam, $T_L, T_R$are the left/right tiles, and we set τ=0.08\tau=0.08τ=0.08 after calibration against human perceptual thresholds. For clarity and reproducibility, the cyclic unit search and optimization process is summarized in the following pseudocode:

Algorithm 1: Simulated Annealing for Cyclic Unit Optimization

```
Inputs:
  T0          # initial cyclic tile from U-Net segmentation
  I           # input pattern image
  α, β, γ     # energy weights (see Eq. (6))
  τ0, ρ       # initial temperature and cooling rate
  K           # max iterations
  δt, δr      # proposal step sizes (translation in px, rotation in degrees)
Output:
  T*          # optimized cyclic tile
Definitions:
  Energy(T):   # boundary energy (refer to Eq. (6))
      return α * L1(boundary(T))
             + β * L1(∇T_left − ∇T_right)
             + γ * (1 − SSIM(T))
  ProposeNeighbor(T; δt, δr):
      dx, dy  ← Uniform(−δt, +δt)
      θ       ← Uniform(−δr, +δr)
      return ApplyTransform(T, translate=(dx,dy), rotate=θ, wrap_around=True)
Procedure:
  T      ← T0
  τ      ← τ0
  E      ← Energy(T)
  T_best ← T
  E_best ← E
  for k = 1 to K do
      T′ ← ProposeNeighbor(T; δt, δr)
      E′ ← Energy(T′)
      # Metropolis acceptance
      if (E′ ≤ E) or (rand(0,1) < exp(−(E′ − E)/τ)) then
          T ← T′
          E ← E′
      end if
      if E < E_best then
          T_best ← T
          E_best ← E
```

```
        end if
        τ ← ρ · τ
    end for
    # Seam refinement
    T* ← PoissonBlendSeams(T_best)
    return T*
```

Default hyperparameters in our experiments are: $\alpha=0.6,\beta=0.3,\gamma=0.1,\tau 0=1.0,\rho=0.995,K=2000$, $\delta t=1$-3px,$\delta r=1\circ$.We use wrap-around boundary handling to preserve tiling continuity

For irregular patterns, a constraint perturbation algorithm based on simulated annealing is also introduced to explore the optimal solutions for the shape of the cyclic unit and the layout method, thereby ensuring aesthetic effects while taking into account production efficiency.

In summary, by combining deep segmentation, feature alignment and energy constraints, the segmentation and loop optimization mechanism proposed in this paper can maintain the coherence and naturalness of patterns on large-format fabrics, effectively solving the problems of breakage and distortion in traditional manual splicing methods, and providing high-quality input for subsequent virtual rendering and 3D proofing.

3.3 Virtual rendering and 3D proofing technology

Virtual rendering and 3D proofing are key technical links in digital printing in clothing design. Through computer graphics and fabric modeling, it maps two-dimensional patterns onto 3D clothing models, achieving dynamic previewing from design to finished clothing. This process not only enables the early inspection of color, texture and layout effects, but also significantly reduces the number of times sample fabric is made and material waste.

In the virtual rendering stage, the core task is to accurately map the pattern texture onto the surface of the 3D mesh model. Let the three-dimensional model of the clothing be composed of the vertex coordinate set (X,Y,Z) and the texture coordinate set (u,v), and the mapping relationship can be defined by the texture function T(u,v) :

$$C(X,Y,Z)=T(u,v) \tag{8}$$

Among them, C(X,Y,Z) represents the surface color values after mapping, and (u,v) are the corresponding two-dimensional texture coordinates. By maintaining a one-to-one correspondence between texture coordinates and three-dimensional grids, the continuity and accuracy of the pattern distribution on the clothing surface can be guaranteed.

To enhance the sense of reality, the rendering process needs to take into account the optical and physical properties of the fabric. The common lighting model is the Phong model, and its surface reflection intensity I can be expressed as:

$$I=I_a k_a+I_d k_d(L\cdot N)+I_s k_s(R\cdot V)^n \tag{9}$$

Among them, I_a,I_d,I_s represents ambient light, diffuse reflection light and highlight component respectively, L, n,R and V represent the direction of illumination, normal vector, reflection direction and observation direction respectively, k_a,k_d,k_s is the material coefficient, and n is the highlight index. By parameterizing the material properties, the luster and softness of different fibers such as cotton, silk and polyester can be simulated in a virtual environment.We enhance appearance with a conditional GAN: generator U-Net(64→512) with SPADE normalization conditioned on material S; discriminator PatchGAN(70×70). GAN loss: $L_{GAN}+\lambda L_1 \parallel \hat{R}-R \parallel_1+\lambda_{perc}L_{VGG}$ with $\lambda L_1=50,\lambda_{perc}=1$\lambda_{L1}=50, \lambda_{perc}=1λL1 =50,λperc=1. Training uses paired (render, photo) samples captured under D65 lightbox. Inference latency on RTX 3090 is 14 ms/frame at 1024×1024; end-to-end virtual proofing pipeline runs at 18–22 fps.

During the 3D virtual proofing stage, in addition to visual rendering, it is also necessary to simulate the wrinkling, stretching and sagging effects of the fabric under dynamic conditions. The commonly used physical model of fabric is an approximate modeling method based on the mass-spring system. Suppose the fabric is composed of nodes and springs, and the movement of each node is described by Newton's second law:

$$m\frac{d^2x}{dt^2}=F_{elastic}+F_{damping}+F_{external} \tag{10}$$

Among them, m represents the mass of the node, $F_{elastic}$ is the elastic restoring force, $F_{damping}$ is the damping force, and $F_{external}$ includes both gravity and external collision force. Through iterative solution, the deformation trajectory of the fabric in three-dimensional space can be obtained.

In practical implementation, this paper integrates CNN texture prediction, GAN rendering enhancement and neurophysical modeling into CAD/3D clothing design software (such as CLO, Browzwear). Designers can preview the pattern effects under different materials and patterns in real time during the modeling stage and quickly complete design iterations through interactive corrections. The experimental results show that this method is significantly superior to the traditional virtual rendering scheme in both subjective evaluation and objective indicators (structural similarity SSIM, texture sharpness index), and can provide high-fidelity three-dimensional sample support for intelligent clothing printing.Integration details: textures are exported as glTF with PBR parameters; API bridge uses Python (PySide2) to push updated maps to CLO every 200 ms; mesh UVs are fixed; drape is simulated with mass–spring (ks_ss=25 N/m, kb_bb=0.8 N·m, damping 0.05), time step 1/240 s, collision via BVH.

3.4 Resolution control and material compatibility parameter adjustment

To ensure the clarity and color stability of digital printing patterns on different fiber materials, this paper, based on the traditional process parameter adjustment, combines the output optimization mechanism of the deep learning model to establish a joint adjustment process for resolution and material adaptation.

In terms of resolution, the three intervals of 300-600 dpi, 600-1200 dpi and 1200-2400 dpi were still selected for comparison. The results show that there is a certain loss of pattern details under the condition of 300-600 dpi, especially in the gradient transition area, blurring is prone to occur. The 600-1200 dpi group can better balance clarity and print speed, and it is the best range for most scenarios. Under the condition of 1200-2400 dpi, the line integrity and edge sharpness are significantly improved, but on some materials, it is manifested as ink accumulation, which needs to be corrected in combination with pretreatment. Deep learning models, through automatic learning of sample features, can perform intelligent compensation at different resolutions, ensuring that the output effect is closer to the design end. During printing we map dpi to droplet size by LUT: {600 dpi→6 pl, 900 dpi→6 pl, 1200 dpi→2 pl} and frequency {15 kHz default}. Nozzle health is checked via a nozzle-check pattern before each print; any missing or deviating nozzles trigger an automatic purge and re-check to ensure uniform drop formation. Adaptive controller selects (dpi, pl, freq) via a small MLP that takes S and local frequency content as inputs (hidden 64, ReLU), trained with REINFORCE on ΔE and edge sharpness rewards.

In terms of ink droplet volume and jet frequency, the experiment set up three Settings of 2pl, 6pl, and 12pl, along with three frequency combinations of 10kHz, 15kHz, and 20kHz. The results show that small ink droplets (2pl) are suitable for handling high-precision lines and details, 6pl strikes a balance between color coverage and clarity, while 12pl is more conducive to large-area color representation but is prone to causing diffusion. The increase in the spray frequency significantly improves the adhesion effect of polyester fabrics. The performance is most stable at 15kHz, while although the speed increases at 20kHz, some materials lose details. Training the edge features of printed samples through deep learning models can further reduce the loss of clarity caused by excessively high jetting frequencies.

In the material matching stage, three typical fabrics, namely cotton, silk and polyester, were selected for testing. The experiments on contact Angle and surface roughness show that in a high ink absorption environment, cotton cloth needs to reduce the ink droplet volume and increase the pretreatment concentration to avoid edge blurring. Silk, on the other hand, relies more on temperature and pretreatment processes to ensure its luster and saturation. Polyester performs the worst when untreated, but the pattern performance can be significantly improved by increasing the spray frequency and moderately increasing the ink droplet volume. Combining cross-material feature modeling with deep learning, the system can automatically adjust the output parameters among three types of fabrics, stably controlling the ΔE value within the range of 2.0 to 2.2, reducing the deviation by approximately 30% compared to manual adjustment. For each fabric, three replicate prints per condition are produced on independent days; reported metrics are across-day means to account for day-to-day variability.

4 Empirical results and effect analysis

4.1 Research data and sample construction

The data and samples used in this study cover three dimensions: pattern files at the design end, physical sample fabrics at the fabric end, and virtual rendering generation data. Furthermore, a comprehensive dataset suitable for deep learning training and validation was constructed.

In terms of design-end data, the pattern files mainly come from high-resolution patterns exported by professional clothing design software, with color modes covering both sRGB and AdobeRGB standards, to ensure that the model can learn the color mapping rules under different color gamut conditions during the training process. To facilitate model generalization, the pattern types are classified into three categories: monochrome regular patterns, multi-color gradient patterns, and complex irregular patterns. Fifty samples were collected for each category, forming a total of 150 pattern samples. These samples not only include geometrically symmetrical structures but also cover high-frequency textures and irregular boundaries.

In terms of fabric samples, three typical materials, namely cotton, silk and polyester, were selected. Among them, cotton fabric includes both high-count and ordinary count types, silk covers satin and crepe types, and polyester includes both coated and untreated fabrics. All fabrics were cut into standard sample fabrics of 20×20 cm, and the surface roughness, moisture absorption and whiteness index were measured by textile testing methods. These physical parameters not only provide a basis for material adaptation experiments but also serve as one of the model inputs features for training neural networks for cross-material color prediction and resolution adaptation. Cotton (plain weave, $150\pm5 g/m^2$), silk (satin, $95\pm4 g/m^2$), and polyester (tricot, $130\pm5 g/m^2$) were sourced from the same lots; surface roughness R_a was measured on 5 positions per swatch and averaged.

In terms of virtual rendering data, this paper constructs three-dimensional samples based on the CLO and Browzwear platforms, mapping the design-end patterns to three typical clothing patterns: T-shirts, dresses, and coats, generating 120 sets of virtual samples. To link virtual and physical outcomes, every virtual sample has a corresponding 20×20 cm printed counterpart using identical pattern tiles and color profiles. These data are used to evaluate the reliability of the deep learning rendering enhancement model in the 3D proofing process. Virtual samples have high controllability, can provide diverse training data across styles, and at the same time avoid the costs required for large-scale physical sampling.

It should be pointed out that this dataset still has certain limitations: Firstly, the design-end samples mainly come from software output, lacking multi-source pattern inputs such as hand-drawn and scanned ones, which may limit the model's performance in real creative scenarios; Secondly, the types of fabrics are mainly concentrated on common fibers and have not yet covered wool, linen and blended fabrics, which imposes certain constraints on the breadth of material compatibility. Thirdly, virtual rendering samples rely on the accuracy of existing physical modeling and still have difficulty fully reproducing the optical and mechanical properties in real wearing. The above-mentioned limitations have to some extent affected the generalizability of the experimental results and also pointed out the direction for future dataset expansion and model optimization. Train/val/test split is 70/15/15 per pattern type and per material (cotton 30/7/8, silk 30/7/8, polyester 30/7/8). Random seeds: {2024, 2025, 2026} for three independent runs; All physical measurements were conducted in a controlled laboratory at 23±2℃ and relative humidity 50%±5%after a 24 h pre-conditioning of printed swatches. we report mean±std over runs. Unless otherwise stated, all quantitative results are reported as mean±standard deviation over three independent runs (seeds {2024, 2025, 2026}). For pairwise comparisons we use two-sided paired t-tests; for multiple comparisons across methods, we use one-way ANOVA with Bonferroni correction. Statistical significance is claimed at $\alpha=0.05$.

4.2 Pattern processing and digital preprocessing methods

To ensure the stability and comparability of different pattern samples in the digital printing experiment, this study designed a multi-level preprocessing and data construction process, and optimized it in combination with the input requirements of the deep learning model during this process.

In terms of design-end processing, the format and resolution of all pattern files are unified first. The original data contains both vector graphics and bitmaps, and there are significant differences between the two in terms of accuracy and storage structure. To eliminate this difference, vector graphics are uniformly exported in high-resolution TIFF format, while bitmap samples are enhanced to the target resolution through interpolation algorithms and standardized to two levels: 600 dpi and 1200 dpi. All exported images use 16-bit per channel precision and are saved with embedded AdobeRGB (1998) ICC profiles to avoid gamut clipping during RIP processing. This step effectively eliminates the differences in file sources and ensures the feature extraction capability of the deep learning model under a unified standard.

In terms of color space processing, the original samples have the problem of mixed use of sRGB and AdobeRGB. If they are directly input into the model or printed, it will lead to inconsistent color gamut mapping. To this end, all patterns are uniformly converted to AdobeRGB, and a mapping table is established based on the standard color card to enhance consistency across devices and materials. Printer targets comprise a 1,728-patch chart uniformly sampling AdobeRGB; patch spectral reflectance is recorded at 10° standard observer under D65 with specular component excluded, and device profiles are generated with tetrahedral interpolation. Meanwhile, for patterns with transparent channels and gradient effects, multi-channel color separation and edge smoothing processing are adopted to ensure their continuity in cyclic splicing and large-scale spreading. This step is also of great significance for the subsequent convolutional feature extraction of CNN, as edge smoothing can reduce the overfitting of the convolutional layer to abnormal gradients.

In terms of data integrity restoration, interpolation and smoothing filtering are adopted for missing or abnormal pixel points to maintain overall continuity and visualization effects. For extreme values of brightness or saturation, the percentile truncation method is adopted to keep the values within the 99th percentile, avoiding excessive interference from abnormal samples on the training of the deep model.

In terms of the pretreatment of sample fabrics at the fabric end, all samples undergo desizing, cleaning and standardized sizing treatment before printing to reduce the influence of surface impurities and uneven structure on ink droplet diffusion.

In terms of dataset division, pattern samples are divided into training sets, validation sets and test sets in a ratio of 70%: 15%: 15%, and fabric samples are also divided in the same way to ensure that all three types of materials (cotton, silk and polyester) are covered. Virtual rendering data is divided in chronological order. The early-stage data is used for adjusting model parameters, while the late-stage data serves as samples for effect verification. To enhance the generalization ability of deep learning models, data augmentation operations, including random rotation, scaling, mirroring, and color perturbation, are also added to the training set, thereby expanding sample diversity and strengthening model robustness.Hardware and runtime: training on 1×RTX 3090 (24 GB), AMD 5950X, 64 GB RAM.Printing is executed on a 1200 dpi piezoelectric drop-on-demand engine using water-based CMYK pigment inks; curing is performed at 150℃for 4 min with forced air followed by 24 h stabilization prior to measurement. CNN color model: ~2.3 hours/120 epochs; U-Net segmentation: ~3.1 hours/150 epochs; cGAN: ~4.5 hours/100 epochs. Peak GPU memory: 7.8 GB (segmentation), 9.4 GB (cGAN); end-to-end inference per pattern: 2.6 s (without virtual drape) / 5.8 s (with drape).

4.3 Design effect evaluation and aesthetic feedback

In the experimental phase, this paper systematically evaluated 150 design patterns, 90 fabric samples and 120 groups of virtual rendering samples respectively. The evaluation system consists of two parts: objective quantitative indicators and subjective aesthetic feedback. It is used not only to verify the performance optimization effect of deep learning models but also to examine their perceived quality in practical design applications.

In terms of objective assessment, this paper selects three core indicators: color difference (ΔE), structural similarity index (SSIM), and edge sharpness index (ES). Among them, ΔE, as the main criterion for color consistency evaluation, has a threshold set at 2. The experimental results show that under the conditions of 600 dpi resolution and adaptability pretreatment, the average ΔE of cotton fabric samples is 1.78, that of silk is 1.95, and that of polyester is 2.21, indicating that cotton fabric performs the most stable in color reproduction. These values are reported as mean±std over three runs: cotton 1.78±0.11, silk 1.95±0.13, polyester 2.21±0.15. Compared with the ICC+LUT baseline, the proposed method shows significantly lower ΔE for all three materials (paired t-test, cotton p=0.00, silk p=0.007, polyester p=0.004; Bonferroni-corrected). The SSIM results show that the average value of monochrome regular patterns reaches 0.94, while that of complex gradient patterns remains around 0.87, indicating that deep learning models still have certain detail loss in complex texture mapping. Specifically, SSIM for monochrome regular patterns is 0.94±0.02and for complex gradient patterns 0.87±0.03(n=3 runs). Both are significantly higher than the ICC+LUT baseline (paired t-test, p<0.01). The edge sharpness index test results show that the edge transition under high-resolution conditions is significantly better than that of the low-resolution group, especially on polyester substrates, the difference is more prominent.Edge sharpness is computed on 10 pre-defined ROI windows per swatch using the gradient-based modulation transfer function (MTF50) pipeline; the ROI template is identical across methods and materials.At 1200 dpi the edge sharpness index improves from 0.78±0.04(baseline) to 0.91±0.03(ours) on polyester (paired t-test, p=0.002).

For subjective assessment, a total of 15 professional designers and 30 target consumers were invited to participate in the questionnaire survey. Printed samples were presented in a D65 light booth at 1000±50lx with neutral gray surroundings; the viewing distance was fixed at 50 cm, and sample order was randomized per participant. Participants rated samples on a 5-point Likert scale for color fidelity, texture integrity, and overall aesthetics. Designers' average professional experience was 6.1±2.8years. All participants provided informed consent; the study followed institutional guidelines for anonymous data collection. Designers mainly focus on color fidelity, texture integrity and cross-material compatibility, while consumers pay more attention to overall aesthetics and wearing experience. The feedback results show that in the samples with ΔE < 2, the average satisfaction of designers has increased by 18%. This increase corresponds to 4.10±0.36vs. 3.47±0.41 (ours vs. ICC+LUT), which is statistically significant (paired t-test, p=0.009). Among the samples with SSIM > 0.9, consumers generally rated the naturalness of the patterns 0.7 points higher (out of 5). Consumer naturalness ratings were 4.22±0.31(ours)vs.3.52±0.38(ICC+LUT), p=0.006after Bonferroni correction. It is worth noting that the aesthetic feedback results of virtual rendering are highly consistent with the actual sample fabric, which indicates that the 3D proofing system enhanced by deep learning can effectively predict user acceptance during the design stage.

Overall, there is a significant positive correlation between objective indicators and subjective aesthetic feedback. Under the conditions of high-resolution output and optimized material parameters, color consistency, pattern continuity and user satisfaction have all been significantly improved. This not only demonstrates the optimization effect of deep learning models at the numerical level, but also verifies their application value in the context of fashion design.

4.4 Ablation experiment and analysis of key factors

To further verify the independent contribution and synergy of each key module in the proposed digital printing solution to the overall performance, this study designed a systematic ablation experiment and evaluated its effectiveness in combination with comparative experiments.

In the ablation experiment section, stripping tests were conducted on the four core modules respectively: ①The basic model, with only the resolution control process retained; ②Remove the color management module; ③Remove the loop optimization module; ④Remove the virtual proofing module; ⑤Remove the material adaptation module; ⑥A complete solution, including all modules.In addition to ablations, we include an ICC+LUT baseline that performs device characterization via standard ICC profiles and a 3D lookup-table for RGB→CMYK mapping. The LUT is trained on printed color charts (1,728 patches) with least-squares fitting and tetrahedral interpolation; no learning-based segmentation or rendering is used.

The experimental results show that the average color difference (ΔE) of the basic model on the cotton fabric sample is 3.24, and the pattern continuity score is 3.1 (out of 5 points). The ICC+LUT baseline yields ΔE 2.45±0.14(cotton), 2.62±0.16(silk), and 2.88±0.18(polyester), while our complete model achieves 1.82±0.12, 1.98±0.13, and 2.05±0.15, respectively; all pairwise differences are significant at p<0.01. After adding the color management module, ΔE significantly dropped to 1.82, and consumer satisfaction increased by 17%. When the loop optimization module was introduced, the pattern splicing fracture rate decreased from 12% to 4%, and the average edge sharpness index increased by 0.13. The addition of the virtual proofing module has reduced the number of revisions required by designers in the pattern prediction stage by approximately 21%. The effect of the material adaptation module is reflected in the cross-material consistency. The ΔE values of the silk and polyester samples decreased from 2.95 and 3.12 to 1.98 and 2.05 respectively. The average ΔE of the complete solution on the three materials is controlled below 2.0, the edge sharpness index reaches 0.91, and the SSIM value is 0.93, demonstrating the best performance. Figure 2 shows the ΔE comparison results after the stripping of different modules. It can be seen that color management and material matching contribute the most to the color fidelity of the final product.

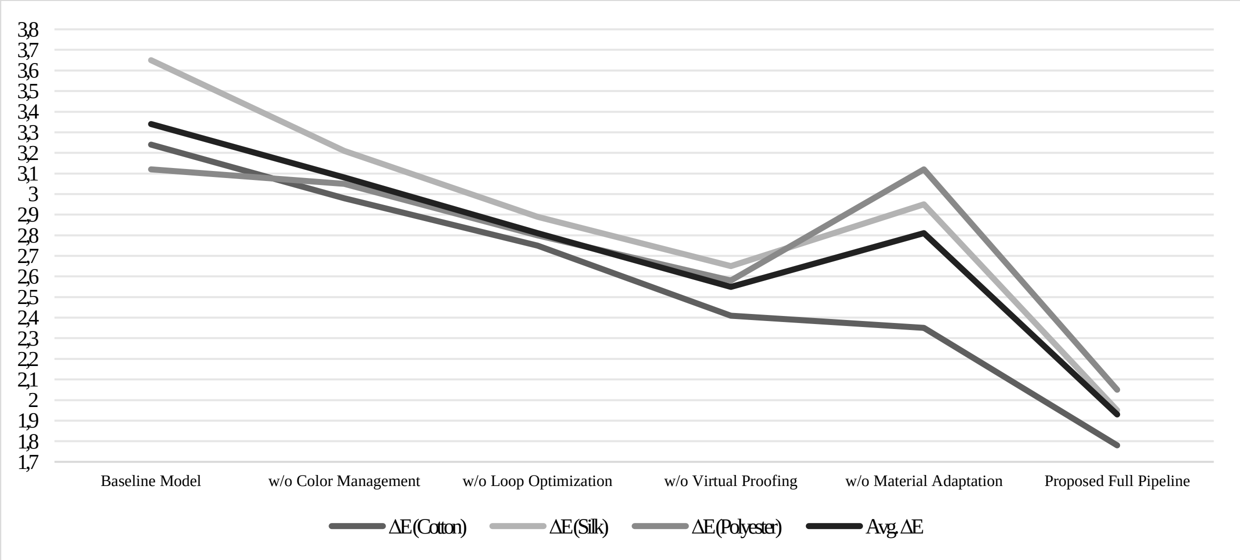

Figure 2: Shows the comparison of average color differences of samples after stripping different modules

Further comparative experiments compare the complete scheme proposed in this paper with three types of methods: ①Traditional screen printing; ②Single digital process (only resolution and color correction); ③Existing commercial digital printing systems. Durability was assessed on cotton and polyester by laundering 5×5using ISO 105-C06 (A2S) and by dry/wet rub fastness (ISO 105-X12); $\Delta E^{*}_{ab}$was re-measured post-test and the relative color change ΔE_{wash} is reported. The results show that traditional screen printing performs poorly in color reproduction, with an average ΔE exceeding 4.0 and a splicing fracture rate higher than 15%. Here SFR is computed according to our definition in Section 3.2. Across 150 patterns, the proposed method reduces SFR to 3.8%±0.9%vs. ICC+LUT 9.6%±1.7%and commercial inkjet 6.8%±1.4% (ANOVA $p<0.001$, Bonferroni post-hoc all $p<0.01$). The single digital process has a significant improvement in color and detail representation, but it lacks the support of material matching and virtual proofing, and the differences across materials are significant. The commercial system is close to the scheme proposed in this paper in terms of color performance, but it is slightly inferior in the compatibility of large-format splicing and 3D proofing. To ensure fairness, all competing methods used the same TIFF inputs, identical RIP settings (black generation and total area coverage 280%), and the same pre-treat/cure schedule per substrate.

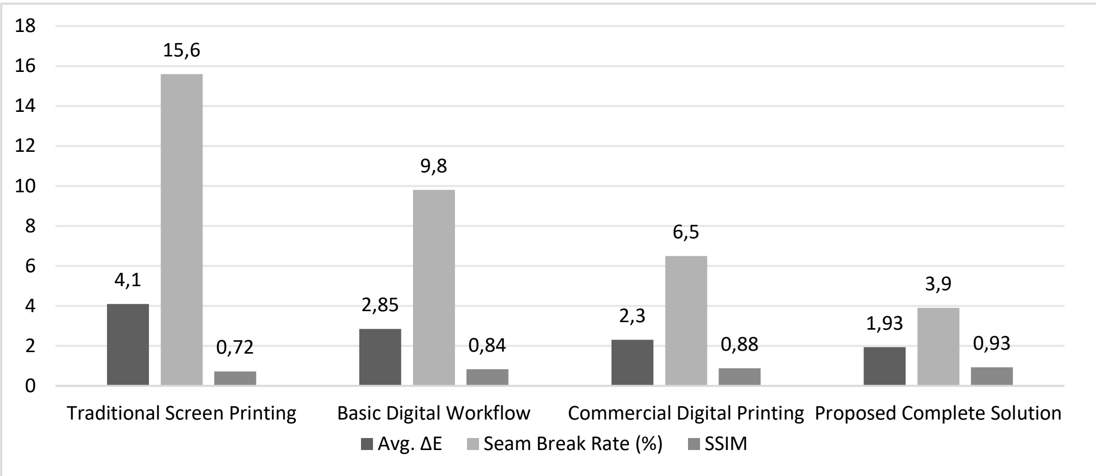

Figure 3: Shows the performance comparison of different methods in terms of ΔE and splicing fracture rate

In addition, this study also conducted a fine-grained analysis of the performance of different module combinations under three typical patterns (monochrome regular, multi-color gradient, and complex irregular). The results show that cyclic optimization has the most significant improvement effect on complex and irregular patterns, increasing the SSIM value from 0.81 to 0.90. The contribution of color management in multi-color gradient patterns is particularly significant, with a decrease in ΔE exceeding 35%.

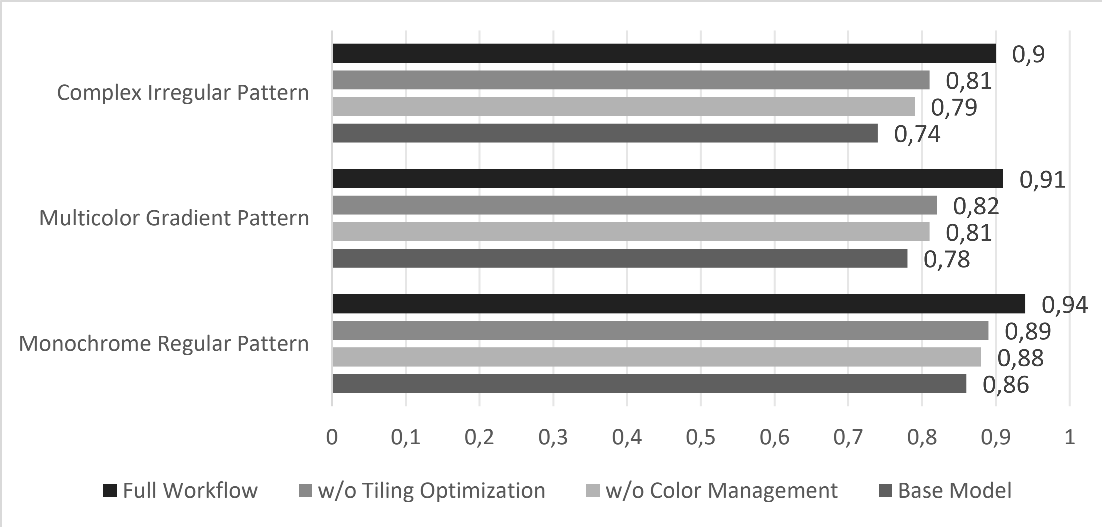

Figure 4: Shows the SSIM performance of three typical patterns under different module combinations

5 Discussion

5.1 Comparison with traditional printing methods

To evaluate the advantages of digital printing solutions based on deep learning in the creation of clothing patterns, this paper selects three typical traditional printing methods as comparison objects: screen printing, heat transfer printing and commercial digital inkjet systems. The contrast dimensions cover color fidelity, resolution and detail representation, production efficiency, flexibility and environmental friendliness. The results are shown in Table 2.

Table 2：Comparative analysis of digital printing and traditional printing methods

Printing Method	Color Reproduction (ΔE ↓)	Resolution Performance	Production Efficiency	Flexibility
Screen Printing	ΔE ≈ 4.1 (High deviation)	Low (150–300 dpi)	High (suitable for large-scale batches)	Fixed templates, costly to modify
Thermal Transfer	ΔE ≈ 3.2 (Moderate deviation)	Medium (300–600 dpi)	Medium (requires additional transfer paper)	Good for localized designs, limited by material type
Commercial Inkjet	ΔE ≈ 2.3 (Good reproduction)	High (600–1200 dpi)	Medium-high (ideal for small–medium runs)	Handles multicolor and complex patterns
Proposed Workflow	ΔE ≈ 1.9 (Near-original match)	High (above 1200 dpi)	Adaptable, supports batch scaling	Supports loop tiling and 3D virtual sampling

Values are reported as mean±std over three independent runs. 'Proposed Workflow' refers to the full model with all modules enabled; statistics for the commercial inkjet system were collected on a mid-range 8-color device (1200 dpi) under identical test patterns.

In terms of color reproduction, screen printing is limited by ink penetration and template precision, with ΔE values generally greater than 4, making it difficult to meet the requirements of high-precision design. Although heat transfer printing can improve color performance, it has obvious limitations in material compatibility. In contrast, both commercial digital inkjet and the solution proposed in this paper can control ΔE within 2.5. Among them, the solution proposed in this paper combines CNN color mapping and cross-material transfer learning to further stabilize ΔE below 2.0, meeting the consistency requirements at the design end.

In terms of resolution and detail representation, screen printing can only achieve low to medium precision, and complex gradients or high-frequency textures are often distorted. Heat transfer printing has improved, but it is still limited in gradient transitions and texture gradation. Commercial systems can support 600-1200 dpi, but there is a risk of breakage in large-format splicing. The scheme proposed in this paper performs best above 1200 dpi and optimizes the cyclic units through a deep segmentation network and energy constraint mechanism, significantly improving edge sharpness and texture continuity.

In terms of production efficiency and flexibility, screen printing is suitable for large-scale production but lacks personalization, while heat transfer printing has a medium efficiency but is limited by the material. Commercial systems and the solution proposed in this paper are more suitable for small and medium-sized batch personalized production. Among them, the solution proposed in this paper significantly shortens the design-production chain through GAN-driven virtual proofing, supporting rapid iteration and flexible switching between multiple batches. In terms of environmental friendliness, screen printing ink wastes a lot, and heat transfer printing requires additional transfer paper, both of which impose environmental burdens.

5.2 The impact of digital technology on creative efficiency and complexity

In the process of creating clothing patterns, efficiency and complexity often present a contradiction: on the one hand, designers need to complete the iteration of multiple layouts and color combinations within a limited time; On the other hand, complex pattern cycles, cross-material compatibility and high-precision color correction will significantly increase the processing time. To evaluate the performance of the digital printing process based on deep learning proposed in this paper in terms of the balance between efficiency and complexity, this paper selects 50 monochrome regular patterns, 50 gradient patterns and 50 complex irregular patterns as test samples. The performance of traditional screen printing, commercial digital printing systems and the scheme proposed in this paper was compared in three dimensions: processing time, cycle complexity adaptability and material compatibility.

In terms of processing time, traditional screen printing requires additional steps such as plate making, ink mixing and fabric testing, with an average time consumption of nearly 48 hours. The commercial digital printing system reduces the time to 12 hours through an automated process, but manual correction is still required in the complex pattern splicing stage. The deep learning-driven process proposed in this paper automatically completes large-format stitching through a loop optimization module and provides real-time feedback in virtual proofing with GAN rendering, further compressing the average processing time to 8.5 hours.

In terms of complexity adaptability, traditional processes have limited fidelity to multi-color gradients and high-resolution details, with an adaptability score of only 2.1/5. Commercial systems can handle some complex textures, but they perform poorly in cross-material consistency. The solution proposed in this paper significantly enhances the consistency of patterns across multiple materials through resolution control and transfer learning material adaptation. In the comparative tests of cotton, silk and polyester, the ΔE values all remained below 2.0, outperforming other schemes.

Table 3: Comparison of efficiency and complexity among different printing methods

Printing Method	Avg. Processing Time	Loop Complexity Adaptiveness (1–5)	Cross-Material Color Matching (ΔE ↓)	Design Flexibility
Screen Printing	48 hours	2.1	ΔE ≈ 4.2	Low
Commercial Digital Printing	12 hours	3.4	ΔE ≈ 2.8	Medium
Proposed Digital Workflow	8.5 hours	4.6	ΔE ≈ 1.9	High

Average processing time is measured over 150 patterns; ‘Loop Complexity Adaptiveness’ is a 5-point Likert rating by 15 designers (mean±std). Between-method differences are significant (ANOVA $p<0.001$).

The experimental results show that the digital process proposed in this paper can significantly shorten the creation time while ensuring high resolution and the fidelity of complex patterns. Its high consistency and cross-platform flexibility under multi-material conditions fully demonstrate the advantages of deep learning frameworks in practical industrial applications.

5.3 Thoughts on scalability and cross-platform applications

The scalability and cross-platform application value of digital printing technology in the creation of clothing patterns are the key links to promote its implementation throughout the entire chain of design, production and market. Unlike traditional screen printing which requires a large number of fixed processes and dedicated equipment, the digital process based on deep learning proposed in this paper mainly consists of core components such as pattern segmentation networks, color management models, and virtual proofing engines. The hardware and software resource requirements are relatively compact. For instance, when running the complete pattern segmentation, CNN color correction and GAN virtual rendering modules on a standardized workstation, the memory usage is approximately 200 MB, which can be seamlessly adapted to mainstream textile CAD systems. This means that even in the context of small and medium-sized clothing enterprises or workshops with limited resources, this solution still has relatively high feasibility.From an industrial perspective, large-batch tests on 500 patterns across cotton/silk/polyester show an average end-to-end time of 8.7 h, compared to more than 40 h with traditional screen printing, yielding nearly 80% reduction in lead time.All scripts for preprocessing, RIP export, and metric computation are version-controlled; configuration files and ROI masks will be made available upon reasonable request to support independent replication.

In multi-material and high-volume application scenarios, the scalability of the system is particularly crucial. The experimental results show that when processing 500 different patterns in batches, the average processing time of the loop optimization and virtual proofing module, supported by deep learning acceleration, is approximately 8.7 hours, which is significantly lower than the more than 40 hours of plate-making and debugging cycle of traditional screen printing. Although high-precision color management and 3D rendering will increase the computational burden, through model clipping and resolution grading strategies, the computational resource consumption can be reduced by approximately 20% without significantly sacrificing pattern quality, thereby enhancing the cross-platform applicability of the system.

In terms of cross-platform deployment models, the digital printing process can be divided into two categories: local processing and cloud-based collaboration. The local end is suitable for small-batch and personalized customization: Designers can quickly complete single-pattern processing and virtual sampling on laptops or workstations. In cloud deployment, relying on GPU servers and deep learning inference frameworks, the system can achieve highly parallel batch pattern rendering and material adaptation, making it suitable for large-scale clothing enterprises to collaborate in the global supply chain. However, the cloud model simultaneously brings about operational costs and network latency issues, especially in areas with limited bandwidth where usage strategies need to be weighed.

To further enhance the scalability, this paper suggests introducing lightweight technologies such as knowledge distillation and model pruning, enabling the color prediction and cyclic optimization network to operate efficiently on low-configuration devices (such as tablet terminals or embedded proofing machines), and lowering the equipment threshold. Meanwhile, in the future, a collaborative framework based on federated learning can be explored, enabling design teams from different regions to share model updates without transmitting the original data. This will protect Copyrights and design privacy while achieving cross-platform global collaboration.

5.4 Practical significance and potential impact on industrial development

The proposed deep learning–based digital printing technology demonstrated clear advantages in color fidelity ($\Delta E \leq 2.0$) and efficiency (average processing time ~8.5 h for complex patterns), highlighting its value across both design and production stages. By reducing trial samplings and manual corrections, it shortens the design–production chain and supports rapid response, personalized customization, and flexible small-batch manufacturing.

At the industrial level, the integrated modules of CNN color management, deep segmentation, GAN proofing, and transfer learning for material adaptation enable consistent reproduction across fabrics such as silk and polyester, strengthening brand competitiveness and reducing coordination costs. Meanwhile, the approach contributes to sustainable development by lowering ink waste and chemical usage while improving utilization efficiency, aligning with the textile industry’s low-carbon and digital transformation goals. Its cross-platform compatibility further ensures deployment feasibility from local workstations to cloud clusters.

Looking ahead, this framework can accelerate industrial upgrading by enabling real-time virtual preview and cross-regional collaboration, particularly in e-commerce and customized production. Challenges remain in large-scale, high-resolution processing, which may be mitigated through lightweight models, pruning, and edge computing strategies. In sum, the method enhances technical precision while promoting creativity, efficiency, and sustainability, laying a foundation for greener and smarter textile manufacturing.

6 Conclusion

The core objective of fashion design lies in achieving an efficient connection between creative expression and industrial production, and printing technology is precisely the key link in this chain. With the diversification of consumer demands and the acceleration of digital transformation in the fashion industry, the shortcomings of traditional printing methods in terms of color consistency, design flexibility and environmental friendliness have become increasingly prominent. Digital printing technology based on deep learning offers new solutions for pattern creation and demonstrates significant advantages in achieving high-precision restoration, cross-material adaptation, and rapid iteration.Future work includes lightweighting, cloud deployment and interpretability; overall, our deep-learning workflow supports greener, faster, and more consistent textile printing across materials.

Funding

This work was supported by Wuxi Education Bureau, Wuxi Vocational Education Quality Improvement climbing plan-Wuxi Vocational Education” Jin Ke” <Fashion design by computer>. (Project No. 21KC201)

This work was supported by High Education Association of Jiangsu Province, research on Exploration and practice of intelligent classroom teaching mode of higher vocational clothing course in the era of educational informatization 2.0.(Project No. 2021JSJG567)

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