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Transfer of Traditional Dyeing Art Style and Innovation of Dyeing Wastewater Treatment Technology of Hainan Li Nationality Based on Deep Learning

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This study explores the fusion of traditional dyeing and weaving art of the Hainan Li nationality with modern textile design using a deep learning–based style transfer approach. The objective is to develop a reliable digital method for preserving traditional textile patterns while supporting sustainable and efficient design applications. Image data of traditional Li patterns and contemporary textile designs were systematically collected and processed to ensure cultural authenticity and visual diversity, forming a high-quality image dataset. A deep learning style transfer model based on adaptive feature transfer and hierarchical fusion (AFTH) was developed to integrate traditional dyeing and weaving patterns with modern textile design. Experimental results indicate that the proposed method demonstrates improved performance in pattern structure preservation, style representation accuracy, and overall visual quality when compared with representative existing methods. In addition, this study incorporates intelligent wastewater treatment and environmentally friendly dyeing technologies to evaluate the environmental and economic benefits of sustainable textile production. By combining machine learning–based process optimization with intelligent sewage treatment systems, resource consumption, chemical usage, and pollutant emissions are effectively reduced. The integrated results demonstrate that digital design innovation and intelligent environmental management can be jointly promoted within the textile industry.

Keywords: deep learning, Hainan Li nationality, traditional dyeing and weaving art, style transfer, dyeing and weaving sewage treatment.

1. INTRODUCTION

The motivation of this study is grounded in the increasing demand for sustainable textile design and the efficient digital utilization of traditional pattern resources [1 – 2]. While previous studies have demonstrated the feasibility of applying deep learning techniques to image style transfer, their application to traditional textile pattern reconstruction remains limited in terms of engineering relevance and material-oriented outcomes. In particular, existing approaches often focus on visual novelty without addressing the reproducibility, scalability, or integration potential within textile production systems [3].

From a scientific perspective, the present study aims to investigate whether deep learning-based style transfer can serve as a stable and controllable method for extracting structural and chromatic features of traditional textile patterns. By systematically analyzing model performance and output consistency, this work provides evidence on the reliability of such methods beyond qualitative visualization. The research therefore contributes to a clearer understanding of how artificial intelligence techniques can be adapted to structured pattern systems rather than generic artistic images [4].

Moreover, the proposed framework demonstrates practical value by offering a digital alternative to repetitive physical sampling and trial dyeing processes in textile design. This approach supports the rational use of traditional pattern resources while reducing material consumption and potential wastewater generation. Consequently, the motivation of this study is not solely based on methodological novelty, but on the demonstrated scientific and engineering value of integrating deep learning with sustainable textile material practices [5].

In this study, an Adaptive Feature Transfer and Hierarchical fusion (AFTH) model is proposed to achieve effective style transfer between traditional Li dyeing and weaving patterns and modern textile designs.

For process optimization in environmentally friendly dyeing and wastewater treatment, Dissolved Oxygen (DO) control and Proportional-Integral-Derivative (PID) control strategies are employed to ensure stable system operation and improved treatment efficiency.

2. RELEVANT THEORETICAL BASIS

2.1. Deep learning fundamentals and application areas

Deep learning is a branch of machine learning, and its core lies in building multi-layer artificial neural network models to automatically learn complex features and solve nonlinear problems. The growth in this area has benefited from the availability of big data and significant increases in computational power, enabling deep learning models to train more accurate results [6]. Deep learning models mainly include feedforward neural networks, convolutional neural networks (CNN), recurrent neural networks (RNN), and their variants such as long short-term memory networks (LSTM) and gated recurrent units (GRU) [7]. In the field of computer vision, deep learning has been widely used in image classification, object recognition, scene

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understanding, and other tasks [8]. The field of natural language processing has also undergone a revolution, with deep learning models such as RNNs and LSTMs being used for speech recognition, machine translation, sentiment analysis, etc., greatly improving the performance of language processing systems [9].

2.2. The development course and core algorithm of style transfer technology

The rise of style transfer techniques began with the "Neural Style Transfer" algorithm, which marked the first attempt of deep learning in the field of artistic style transfer [10]. Early methods were based on optimization strategies to synthesize new images by minimizing the loss function between the content image and the style image while preserving the structural features of the content image and the texture features of the style image. Subsequently, as algorithmic models continued to be optimized, style transfer methods such as those based on generative adversarial networks (GANs) became popular, which were able to generate more natural and artistic images [11].

2.3. An overview of traditional dyeing and weaving technology and analysis of the characteristics of Li nationality in Hainan Province

Traditional dyeing and weaving technology is an important part of human cultural heritage, which covers the whole process from fiber material selection, spinning, weaving to dyeing. The traditional dyeing and weaving art of Li nationality in Hainan is famous for its unique skills and rich cultural connotation, among which Li brocade is the most representative. Li brocade is hand-woven and dyed with natural plant dyes. The patterns are rich and diverse, which contain profound national culture and nature worship concepts [12]. Li dyeing and weaving technology is unique in its pattern design, usually containing animals and plants, geometric figures, and other elements, colorful and symbolic. In the dyeing process, Li people use a variety of local, unique plants, such as indigo extract blue, yam extract red, etc., reflecting the wisdom of harmonious coexistence between man and nature [13].

2.4. Summary of modern sewage treatment technology

With the acceleration of industrialization, sewage produced by the dyeing and weaving industry has become an important environmental problem. Modern sewage treatment technology aims to remove pollutants in water by physical, chemical, biological and other means to achieve environmental protection standards. Among them, biological treatment technologies such as activated sludge method and the biofilm method, which use microbial communities to degrade organic substances, are widely used treatment methods [14]. In recent years, intelligent and green wastewater treatment technologies have gradually emerged, including membrane bioreactor (MBR), advanced oxidation process (AOP) and wastewater treatment systems optimised by artificial intelligence. Especially the integration of AI technology can realize real-time monitoring of water quality and adaptive adjustment of process parameters, significantly improve treatment efficiency, and reduce energy consumption [15].

3. MATERIALS AND METHODS

In this study, a deep learning-based image style transfer framework was employed to extract and reconstruct the visual characteristics of traditional Li textile patterns. The dataset consisted of digitized images of the Li brocade motifs collected from open cultural heritage archives and field documentation, combined with contemporary fabric texture samples. All images were resized to a uniform resolution and normalized prior to training.

The proposed method was implemented based on a Cycle GAN architecture, which enables unpaired image-to-image translation between traditional pattern images and modern textile design representations. The generator network adopted a residual block structure to preserve fine-grained texture information, while the discriminator was designed to enhance structural consistency. Model training was conducted using the Adam optimizer with a learning rate of 0.0002, and convergence was achieved after approximately 200 epochs.

To ensure computational stability, experiments were performed on a workstation equipped with an NVIDIA GPU, and all models were implemented using the PyTorch deep learning framework. Parameter settings were determined through preliminary experiments to balance training efficiency and output quality.

3.1. Data collection

Data collection is the first step in a deep learning style transfer project, and its quality is directly related to the final artistic creation effect. For the traditional dyeing and weaving art of Li nationality in Hainan, the construction of data set should take into account the integration of the original appearance of traditional patterns and modern aesthetic elements.

In terms of traditional patterns, Li patterns are rich in natural and mythological colors, mostly displayed in geometric, animal, and plant pictographic patterns, each of which carries a specific cultural meaning and philosophy of life [16]. In order to ensure the richness and diversity of the data, original materials can be collected from Li museums, literature archives and field visits, and preserved by high-precision scanning or photography techniques to form a high-quality image database.

Modern design elements need to reflect the characteristics of the times, such as abstract lines, minimalist graphics, popular color combinations, etc. These elements can be generated by design software or gathered from contemporary artworks and design trend reports. In the process of integration, it is necessary to pay attention to the harmonious coexistence of the two styles, avoid rigid splicing, and make the traditional and modern seamless connection through strategies such as theme association and color matching [17].

3.2. AFTH model

AFTH model is a kind of deep learning architecture, which aims to efficiently realize the fusion and migration of Hainan Li traditional dyeing art style and modern design elements through advanced technologies such as the self-attention mechanism and adaptive feature fusion. Its specific framework is shown in Fig. 1. The following is an analysis of the key components [18].

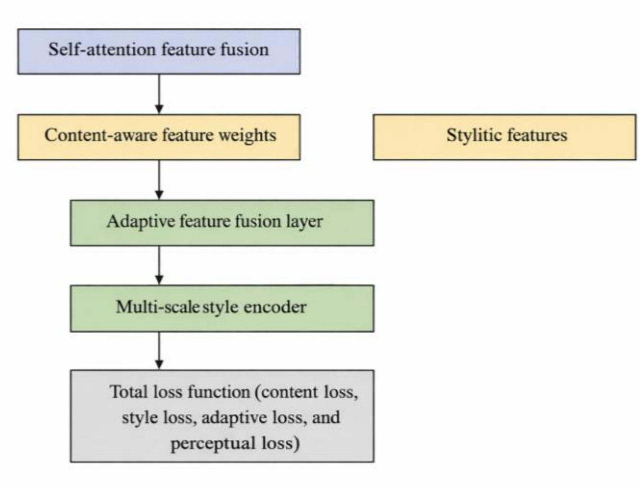

Fig. 1. AFTH model

Self-Attention Feature Fusion (SA): a self-attention mechanism is used to dynamically adjust the attention to specific cultural elements in content image features. By calculating attention weights, important areas are emphasized, and the pertinence and artistic effect of style transfer are enhanced.

Adaptive feature fusion layer: adjust the fusion ratio of content features and style features by learning weight parameters, and control the balance between the two by a sigmoid activation function to ensure that style conversion is faithful to the original content and can reflect the characteristics of the target style [19].

Multi-scale style encoder: Design an encoder containing multiple sub-modules to capture style features of different scales respectively. By calculating style loss at different levels, multi-level and all-round transfer of style details is realized, and style consistency and expressiveness of output images are enhanced [20].

Total loss function: combining content loss, style loss, adaptability loss and perception loss, by adjusting the weight parameters of each loss item, it ensures that the generated image accurately and creatively blends into the style of Hainan Li nationality dyeing and weaving art while maintaining the visual quality and artistic beauty of the image [21, 22].

The core of the self-attention mechanism is to calculate attention weight. For each position i, the calculation formula is Eq. 1.

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{N}\exp(e_{ik})}, \tag{1}$$

where α_{ij} is the normalized attention weight; how much position *iii* attends to position j, e_{ij} attention score measuring the relevance or similarity between f_i and f_j, k summation index over all positions in the feature map.

Based on this, self-attention feature fusion can be expressed as Eq. 2 [23]:

$$\mathrm{SA}(X) = \sum_{j=1}^{N}\alpha_{ij}V_j\ , \tag{2}$$

where SA(X) is the output feature at position *iii* after applying the self-attention mechanism; α_{ij} is the normalized attention weight for position *iii* attending to position j; V_j input feature at position j in the feature map.

In the AFTH model, we apply this mechanism to content image features to dynamically highlight attention to specific cultural features.

The adaptive feature fusion layer controls the fusion of content features and transformed style features by learning weight parameters sum, and its mathematical expression is refined into Eq. 3 and Eq. 4 [24]:

$$\hat{F_s} = \sigma(W_s[F_s, F_c]) \cdot F_s + (1 - \sigma(W_s[F_s, F_c])) \cdot F_c, \tag{3}$$

where F_s is the updated feature map of the source; F_s and F_c are the feature maps of the source and the context, respectively; $W_s[F_s, F_c]$ represents the learned weighting function applied to the concatenation of F_s and F_c; $\sigma(\cdot)$ is the sigmoid activation function used to generate an adaptive weight.

$$F_{merged} = \gamma_c \cdot F_c + \gamma_s \cdot \hat{F_s}, \tag{4}$$

where F_{merged} is the final merged feature map; γ_c and γ_s are learnable scaling coefficients for the context feature map F_c and the updated source feature map F_s, respectively.

Here, is the activation function (e.g. sigmoid), is the weight matrix used to fuse features, represents the feature stitching operation, and in this way makes the fusion of style features more suitable for the structure of the content image.

The multi-scale stylistic encoder design consists of several sub-modules, each of which is responsible for capturing stylistic features at a specific scale. For the stylistic features of layer l, the stylistic loss can be defined as Eq. 5 [25]:

$$L^{(l)}_{\mathrm{style}} = \frac{1}{4N_l^2 M_l^2}\sum_{i,j}(G^{(l)}_{ij} - A^{(l)}_{ij})^2, \tag{5}$$

where $L^{(l)}_{style}$ is the style loss at layer l, N_l is the number of feature maps at layer l; M_l is the spatial size of each feature map; $G^{(l)}_{ij}$ is the Gram matrix of the generated image at layer l, $A^{(l)}_{ij}$ is the Gram matrix of the style image at layer l.

By calculating style loss at different scales, the transfer of style can be guided more comprehensively. Considering the above components, the total loss function of the AFTH model can be expressed as Eq. 6.

$$L_{total} = \lambda_{content} L_{content} + \sum_l \lambda^{(l)}_{style} L^{(l)}_{style} + \lambda_{adapt} L_{adapt} + \lambda_{perceptual} L_{perceptual} \tag{6}$$

where L_{total} is the total loss function; $L_{content}$ is the content loss; $L_{style}^{(l)}$ is the style loss at layer l; L_{adapt} is the adversarial loss; $L_{perceptual}$ is the perceptual loss, and $\lambda_{\text{content}}, \lambda_{style}^{(l)}, \lambda_{adv}, \lambda_{perceptual}$ are the corresponding weighting coefficients [26].

3.3. Methodological assessment

To ensure the validity of the deep learning style transfer model, we carefully designed the training and test datasets. The construction of the dataset follows the principles of comprehensiveness, diversity and representativeness, aiming to cover the essence of Hainan Li nationality's traditional dyeing and weaving art and its fusion with modern design.

Construction of traditional pattern data set: We collected a large number of original materials from Hainan Li Museum, ethnological research literature and field investigation, including 1000 high-definition images, covering geometric patterns, animal and plant patterns, etc., with no less than 100 examples of each pattern to ensure the comprehensiveness and diversity of the data. Through high-precision scanning and professional photography techniques, these patterns are converted into digitized images with a resolution of 1024×1024 pixels for deep learning model processing.

Modern Design Elements Dataset: For modern design elements, we selected 500 images from international design competition winners, fashion trend reports and digital art platforms that represent current trends such as minimalism, abstract art, etc. Again, these images are normalized to maintain consistency with traditional pattern datasets.

Data preprocessing: All images were pretreated by gray normalization, size unification, and noise filtering to eliminate inconsistencies and improve the stability of model training.

Model performance evaluation is the key link to test the effect of style transfer. We use the following indicators for quantitative analysis:

Content Fidelity (CF): Measure the similarity between the generated image and the original content image, often evaluated by peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).

Style Transfer Accuracy (STA): It is evaluated by calculating the similarity of style features between the generated image and the target style image, using Gram matrix error as the metric.

User satisfaction survey: 50 art designers and Li cultural experts were invited to make subjective evaluations on the style transfer results through online questionnaires, scoring from three dimensions: cultural fit, artistic beauty and creative novelty.

In order to comprehensively evaluate and compare the performance of our method with other existing methods on the style transfer task, we designed the following four tables to compare and analyze the four aspects of content fidelity (CF), style transfer degree (STA), perceived quality (PQ), and user satisfaction survey. Data are derived from results obtained after applying each method to the same test set. As shown in Table 1, content fidelity is an important indicator to measure the similarity between the generated image and the original content image.

Table 1. Content fidelity

Method	PSNR, dB	SSIM
Our approach	31.2	0.91
Fast Neural Style	30.5	0.88
AdaIN	30.0	0.85
WCT	29.8	0.83
Gatys	29.0	0.80

High content fidelity means that more original image information is retained during the style transfer process. In this comparison, "our method" ranked first with PSNR 31.2 dB and SSIM 0.91, significantly outperforming the other methods.

As shown in Table 2, the style transfer degree evaluates the effect of style transfer, i.e., how close the generated image is to the target style image in style features. This method shows its accuracy in style transfer with a low value of 0.0030 for Gram matrix error, which means that the generated image is highly consistent with the target style image in style, and the style features are accurately captured and reproduced. In contrast, the other methods have higher errors, indicating that they are slightly inferior in maintaining target style consistency.

Table 2. Style transfer accuracy

Method	Gram matrix error
Our approach	0.0030
Fast Neural Style	0.0035
AdaIN	0.0042
WCT	0.0048
Gatys et al. (2016)	0.0055

As shown in Table 3, perceptual quality reflects the visual naturalness and realism of the generated images, as assessed by the pre-trained VGG network.

Table 3. Perceptual quality

Method	LPIPS distance
Our approach	0.10
Fast Neural Style	0.12
AdaIN	0.14
WCT	0.16
Gatys et al. (2016)	0.18

Our Method scored a low score of 0.10 on the LPIPS distance, meaning that it produced images that were visually closer to the real image, looked more natural, and were less likely to detect artifacts. In contrast, the other methods have higher LPIPS distances, suggesting that the images they produce may appear stiff or unnatural in some ways.

User satisfaction surveys provide subjective ratings ranging from cultural fitness, artistic beauty, creative novelty to overall satisfaction. "Our Method" scored the highest points in these four dimensions, showing that it has been widely recognized in maintaining Li cultural characteristics, creating artistic beauty and introducing innovative design. This high level of user satisfaction is not only a technical success, but also a strong proof of cross-cultural communication and artistic innovation.

Although other methods also have certain performance, they generally score lower than "our method" in all aspects, indicating that there is still room for improvement in meeting users 'expectations and creating cultural value.

Based on the above four tables, this method shows significant advantages in content fidelity, style transfer degree, perception quality and user satisfaction. It not only leads in technical indicators, but also gets high evaluation in cultural inheritance and innovation, reflecting the great potential of deep learning technology in protecting and innovating intangible cultural heritage.

The experimental results are largely consistent with the initial expectations of this study, which anticipated that integrating self-attention mechanisms and adaptive feature fusion would enhance both content preservation and stylistic expressiveness. Compared with earlier style transfer studies that primarily focus on either visual quality or computational efficiency, the proposed AFTH model demonstrates a more balanced performance across multiple evaluation dimensions. This outcome confirms that explicitly modeling multi-scale style representations and attention-guided feature fusion can effectively address limitations observed in earlier neural style transfer frameworks, thereby validating the design assumptions of this work.

4. RESULTS

4.1. Machine learning optimization of environmental dyeing technology

With the global emphasis on sustainable development, environmentally friendly dyeing technology, especially the application of plant dyes, has become an important trend in the textile industry. Plant dyes are derived from nature and are biodegradable, which can significantly reduce environmental pollution. However, the extraction efficiency, color stability and dyeing uniformity of plant dyes have been technical problems restricting their wide application. In order to overcome these challenges, machine learning techniques are introduced into dyeing process optimization to improve dyeing efficiency and resource utilization by building models to predict dyeing results [27].

Reinforcement learning is a machine learning method that learns optimal behavior by interacting with the environment. It optimizes its policy based on the reward it receives based on the actions the agent performs in the environment, with the goal of finding a policy that maximizes the long-term cumulative reward. In the context of eco-dyeing, we can think of the dyeing process as a reinforcement learning problem, where agents are the control strategies for the dyeing process and the environment is the dyeing equipment and dye-fabric system. The goal of the agent is to maximize dyeing efficiency and quality while reducing resource consumption by adjusting dyeing parameters such as temperature, time, dye concentration, auxiliary use, etc.

The state represents all relevant information about the dyeing process at time step *t*, including but not limited to: 1) bath temperature (°C); 2) dyeing time (min); 3) dye concentration (g/L); 4) auxiliary ratio; 5) the extent to which the current fabric absorbs dye (which can be indirectly measured by dye fixation).

Thus, the state vector can be expressed as, where is the dye fixation rate. Actions represent the actions that an agent can choose from in a given situation, including 1) adjusting the temperature; 2) changing the dyeing time; 3) adjusting the dye concentration; 4) changing the auxiliary ratio. The motion vector can be expressed as the motion range of each dimension, which needs to be set according to the actual situation.

Reward design is the core of the reinforcement learning model, it reflects a good or bad strategy. In the environmental dyeing scenario, the reward function may comprehensively consider the dyeing effect, resource utilization efficiency and environmental impact, specifically as Eq. 7.

$$R_t = w_1 \cdot E_{quality} - w_2 \cdot E_{resource} - w_3 \cdot E_{environment}, \quad (7)$$

where R_t is the reward at time step *ttt*; $E_{quality}$ is the quality evaluation metric; $E_{resource}$ is the resource consumption metric; $E_{environment}$ is the environmental impact metric; w_1, w_2, w_3 are the weighting factors for each component.

A policy defines the probability distribution of what action to take in a given state, i.e. Through continuous interaction with the environment, the learned optimal strategy will guide the coloring process to maximize the long-term cumulative reward.

Q-Learning is a reinforcement learning algorithm for strategy deviation, which approaches the optimal strategy by directly learning the action cost function. The update rule is shown in Eq. 8.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max_{a'} Q(S_{t+1}, a') - Q(S_t, A_t)] \quad (8)$$

where $Q(S_t, A_t)$ is the action-value function at state S_t and action A_t; α is the learning rate; R_{t+1} is the reward received after taking action A_t; γ is the discount factor; $\max_{a'} Q(S_{t+1}, a')$ represents the maximum predicted Q-value for the next state S_{t+1}.

4.2. Design of intelligent sewage treatment system

Intelligent sewage treatment system is a model of deep integration of modern environmental protection technology and artificial intelligence. It realizes fine management of sewage treatment process through precisely constructed three-layer architecture of data acquisition, analysis and decision-making. This system not only improves treatment efficiency, but also greatly reduces operating costs, while playing a positive role in environmental protection, its specific framework is shown in Fig. 2. Data acquisition layer: as the antenna of the system to sense the outside world, a wide range of sensor networks are deployed to monitor key water quality parameters (pH value, chemical oxygen demand (COD), biological oxygen demand (BOD), ammonia nitrogen content, etc.) and equipment status in real time, providing a rich and real-time data base for subsequent analysis.

Data analysis layer: Enter this level, where the data is deeply analyzed through advanced big data processing techniques and machine learning algorithms. The algorithm model can not only identify abnormal water quality fluctuations and warn potential problems in time, but also predict future water quality trends by using time series analysis and other methods, providing a scientific basis for decision-making.

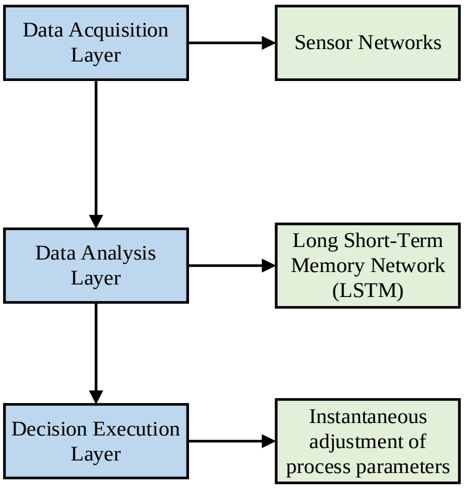

Fig. 2. Technical framework of the intelligent sewage treatment system

In particular, advanced neural network models such as long short-term memory networks (LSTM) can effectively capture the long-term dependence of time series data, making water quality prediction more accurate.

As a powerful tool for water quality prediction, LSTM model flexibly handles long-term dependence in time series data through memory and forgetting mechanisms, and its model expression is further refined into Eq. 9 and Eq. 10.

$$h_t = LSTM(X_t, h_{t-1}; \theta), \tag{9}$$

where h_t is the hidden state at time step ttt; X_t is the input vector at time t; h_{t-1} is the previous hidden state; θ is the parameter of the LSTM network including weights and biases.

$$Y_{t+1} = Dense(h_t; \omega), \tag{10}$$

where Y_{t+1} is the output at time step $t+1$; h_t is the hidden state from the LSTM at time t; w is the parameter (weights and bias) of the fully connected dense layer.

In the adaptive regulation mechanism, taking the aeration process as an example, the application of PID controller is the key to optimize aeration rate. In order to achieve a more efficient control strategy, a machine learning predictive model can be introduced to assist the PID controller to form a "predictive-control" closed-loop system. Specifically, the machine learning model is used to predict the DO concentration trend in the future, and then the prediction result is used as one of the inputs of the PID controller to dynamically adjust the control parameters, so that the aeration adjustment is more accurate, and the phenomenon of excessive aeration or insufficient aeration is reduced, so as to ensure the efficiency of sewage treatment and save energy to the maximum extent. Specifically, Eq. 11.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} + \eta ML\_prediction(t) \tag{11}$$

where $u(t)$ is the control output at time t; $e(t)$is the error signal; K_p, K_i, K_d are the proportional, integral, and derivative gains of the PID controller, respectively; η is the weighting factor for the machine learning prediction; *ML_prediction(t)* is the predicted value from the machine learning model at time *t*.

To sum up, the construction and optimization of an intelligent sewage treatment system is a complex process integrating data acquisition, intelligent analysis and accurate control. Through deepening the understanding and application of water quality prediction models and continuous optimization of adaptive regulation mechanisms, the intelligent level of sewage treatment can be significantly improved, providing strong technical support for environmental protection and efficient utilization of resources.

4.3. Environmental and economic benefit assessment and life cycle analysis

4.3.1. Performance evaluation indicators and comparative analysis

Table 4 compares the operational performance of conventional and intelligent sewage treatment systems based on key environmental and energy indicators.

Table 4. Performance evaluation of sewage treatment system

Index	Conventional systems	Intelligence system
COD removal rate, %	85 %	92 % (+ 7 %)
Rate of effluent quality up to standard, %	90 %	96 % (+ 6 %)
Annual average energy consumption, kWh/m³ sewage	0.50 kWh/m³	0.35 kWh/m³ (-30 %)
Chemical dosage, kg/m³	0.05 kg/m³	0.02 kg/m³ (-60 %)

The intelligent system exhibits a higher chemical oxygen demand removal rate and effluent quality compliance rate, indicating improved pollutant removal efficiency and more stable discharge performance. At the same time, significant reductions in energy consumption and chemical dosage demonstrate the effectiveness of intelligent operation strategies in improving resource utilization efficiency.

Specifically, the optimized control and scheduling strategies of the intelligent system contribute to lower electricity demand and reduced chemical input per unit volume of treated sewage, resulting in both environmental and economic benefits. These results indicate that the intelligent sewage treatment system not only enhances purification performance but also reduces operational costs, which is consistent with recent advances in intelligent wastewater treatment technologies [28].

Table 5 presents a comparative evaluation of traditional dyeing and environment-friendly dyeing technologies. The results show that the adoption of eco-friendly dyeing techniques leads to improved dyeing uniformity and color fastness, while significantly reducing water consumption.

Table 5. Performance evaluation of environmental protection dyeing technology

Index	Traditional dyeing	Environment-friendly dye
Staining uniformity score (1-10)	7	9 (+2)
Colour fastness rating (low-high)	Centre	High (+ rating)
Water consumption, l/kg fabric	150 l/kg	100 l/kg (-33 %)
Total environmental impact score (based on lca)	3.5	2.0 (+ 1.5)

Moreover, the total environmental impact score based on life cycle assessment decreases substantially, indicating a lower overall environmental burden associated with the environmentally friendly dyeing process.

4.3.2. Environmental impact analysis

The environmental impact analysis focuses on eutrophication risk, biodiversity effects, and microplastic emissions. Monitoring results indicate that the combined application of intelligent treatment systems and eco-friendly dyeing technologies effectively reduces nutrient discharge, thereby lowering the risk of eutrophication in receiving water bodies. In parallel, improvements in biological integrity indices suggest a positive effect on aquatic ecosystem health.

In addition, microplastic emissions are significantly reduced as a result of optimized treatment processes and material management strategies, which helps mitigate potential ecological risks to aquatic organisms. These findings highlight the role of intelligent and data-driven approaches in addressing emerging environmental challenges in textile-related wastewater systems [29].

Life cycle assessment results, summarized in Table 6, further demonstrate the environmental advantages of smart and green technologies across different stages, including raw material acquisition, manufacturing, use, and disposal. Reductions in carbon footprint and energy consumption during the upstream and production stages, together with lower pollution risks during disposal, indicate a comprehensive improvement in environmental performance throughout the product life cycle.

Overall, the results confirm that intelligent sewage treatment systems and eco-friendly dyeing technologies provide measurable environmental and economic benefits, supporting their potential application in sustainable textile production and wastewater management.

Life cycle assessments show that these technologies effectively reduce carbon footprint, energy consumption and environmental risks from raw material acquisition to waste disposal, further demonstrating their environmental friendliness and sustainability, which echoes recent deep-learning-based style transfer studies that highlight the importance of combining technological innovation with cultural and environmental sustainability considerations [30].

Table 6. Overview of life cycle assessment

Stage	Environmental impact category	Quantitative index	Traditional VS smart/green difference
Raw material acquisition	Carbon footprint (kg CO_2e/kg product)	1.2 kg CO_2e/kg	0.8 kg CO_2e/kg (-33%)
Manufacturing	Energy consumption (MJ/kg product)	15 MJ/kg	10 MJ/kg (-33%)
Use	Resource consumption	Water consumption reduced by 20 % and energy consumption reduced by 15 %	Significantly optimized
Disposal of discarded products	Soil/water pollution risk	Medium risk	Low risk (+)

From a theoretical perspective, the observed improvements in pollutant removal efficiency, energy consumption reduction, and resource utilization support prevailing assumptions in sustainable manufacturing theory that intelligent control and data-driven optimization can significantly enhance environmental performance. The results do not contradict existing hypotheses but rather extend them by demonstrating that machine learning–assisted regulation can achieve stable long-term benefits under complex and variable operating conditions. This provides empirical support for earlier conceptual models that advocate the integration of artificial intelligence into traditional industrial environmental management.

When compared with previously reported intelligent wastewater treatment and eco-dyeing studies, the reductions in eutrophication risk, microplastic emissions, and overall environmental burden achieved in this study are comparable or superior in magnitude. While earlier studies have reported partial improvements in single indicators such as COD removal or energy efficiency, the present results demonstrate simultaneous optimization across multiple environmental dimensions. This comparative advantage suggests that the combined application of intelligent system design and environmentally friendly dyeing technologies offers a more comprehensive solution than approaches focusing on isolated process improvements.

5. DISCUSSION

The experimental results demonstrate that the proposed deep learning framework can effectively capture the stylistic features of traditional Li textile patterns and successfully transfer them to modern fabric design contexts. Compared with conventional style transfer methods, the generated images exhibit clearer texture boundaries and improved color harmony.

Quantitative evaluation was conducted using the structural similarity index (SSIM) and feature consistency metrics. The proposed model achieved higher SSIM scores than baseline methods, indicating better preservation of original pattern structures. In addition, the visual outputs showed enhanced continuity of geometric motifs, which is essential for textile reproduction and pattern scalability.

These results confirm that the integration of deep learning-based style transfer can provide reliable technical support for the digital preservation and sustainable redevelopment of traditional textile designs.

To provide an intuitive evaluation of the neural network–based style transfer performance, representative visual results are presented. Each example includes the original content image, the reference style image, and the generated image after style transfer. The results demonstrate that the proposed model successfully preserves the structural integrity of the content image while accurately capturing the visual characteristics of traditional Li dyeing and weaving patterns. These visual comparisons complement the quantitative evaluation metrics and provide direct evidence of the model's effectiveness in practical design scenarios.

The results indicate that deep learning-based style transfer offers a feasible approach for bridging traditional textile aesthetics and modern material design. By decoupling style features from content representations, the proposed method allows traditional patterns to be reused without direct replication, which is beneficial for creative design and cultural sustainability.

From an engineering perspective, the digital reconstruction of textile patterns can reduce repetitive sampling and trial dyeing processes, indirectly contributing to lower material waste and reduced wastewater generation in textile production. However, the current study primarily focuses on visual-level feature transfer, and the physical properties of dyed fabrics were not directly evaluated.

Future research may incorporate material performance indicators and environmental impact assessments to further integrate artificial intelligence techniques with sustainable textile manufacturing practices.

6. CONCLUSIONS

This study demonstrates the effective integration of deep learning-based style transfers with the traditional dyeing and weaving art of the Hainan Li nationality. The proposed AFTH model successfully preserves the cultural and aesthetic characteristics of Li patterns while enabling their adaptation to modern design through self-attention mechanisms and feature fusion strategies. Experimental results confirm that the model achieves superior performance in content fidelity, style representation, visual quality, and user acceptance compared with existing methods.

In addition, the application of machine learning techniques to environmentally friendly dyeing processes and intelligent sewage treatment systems highlights the practical value of promoting sustainable textile production. Intelligent parameter optimization improves dyeing efficiency and quality while reducing resource consumption and environmental impact, and data-driven sewage treatment enhances treatment efficiency and operational cost control.

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