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Design and Visual Expression of a Digital Textile Pattern Generation System Based on Traditional Chinese Patterns

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ABSTRACT

Traditional Chinese patterns encounter challenges in contemporary textile design in terms of low production efficiency, an insufficient amount of precision, and a lack of innovation. In response, this paper designs a digital patterned textiles generation system. Specifically, this system extracts geometric structures and colors using a convolutional neural net (CNN) and a residual net. The system implements a conditional generative adversarial network (cGAN) that generates features based on a combined feature vector and conditional information during generation to ensure consistency of style. Finally, an adaptive style transfer algorithm is used to fine-tune lines, colors, and textures by optimizing a combination of content loss, style loss, and edge preservation loss. The patterns are finally enhanced through high-frequency reconstruction using a super-resolution convolutional neural net (SRCNN) to aid clarity and high-resolution patterns. The experimental results show the generated pattern achieves a structural similarity (SSIM) index of 0.99, a peak signal-to-noise ratio (PSNR) of 37 dB, a sharpness index of 0.95, and accuracy of geometric elements representation in cultural symbols with up to 98% accuracy. This work successfully enables the innovative integration of the digital inheritance of traditional patterns and contemporary textile design.

KEYWORDS

digital design, traditional patterns, generative adversarial network, image processing, cultural symbols

INTRODUCTION

Traditional Chinese patterns, as vital components carrying cultural symbolization in textile design, entail deep artistic value and social significance. How to maintain traditional cultural meaning while achieving innovation, as part of the digitalization and intelligentization development of the textile industry, has become a relevant topic needing attention in the design practice [1,2]. Transforming traditional patterns into efficient, precise, and diverse expressive patterns through digital technology helps promote modern inheritance of cultural traditions and a key moment for design innovation in the textile industry [3,4]. The production process for traditional handmade patterns is ultimately limited by the inconsistent efficiency, accuracy of reproducing details of the pattern, and limited opportunity for innovation during the production process [5,6]. Hand painted patterns revert back to the skills of the artist, ultimately affecting the ability to maintain a regular geometric structure as well as levels of color. In production for textiles, hand painted patterns are often transferred, without standardization, production often compromises the level of precision and resolution expected with modern textile [7,8]. Finally, there is limited flexibility in style variation, with optimizing details for pattern breaks in the imagining stage becoming problematic in relation to modern aesthetics and approaches to diverse applications [9,10]. In recent years, the emergence of computer-aided design and artificial intelligence tools has led development efforts to explore ways to further improve the generation quality and optimization of traditional patterns through various processes [11,12]. There has been some advancement within image processing types of reconstruction methods that can yield moderate improvements in feature extraction and contour restoration; however, both are relatively limited with respect to detail preservation and color consistency [13,14]. Feature extraction types of methods relying on convolutional neural networks have captured geometric and texture information adequately for pattern analysis, although they can also be relatively unstable at times when the process involves more complex styles of transfer [15,16]. There has been notable research regarding utilizing generative adversarial networks to generate patterns, however, the state-of-the-art research mostly focuses on visual fidelity and low fidelity/precision to maintain cultural symbols, while not exploring the degree of detail adaptation and fidelity transfer. Style transfer methods have achieved outstanding results in artistic expression, but have shortcomings in optimizing the pattern's line direction and color distribution. While these studies have promoted the digitization of traditional patterns, a complete technical system that balances cultural expression, detail accuracy, and production standards has yet to be established.

To address the problems of insufficient precision, poor style adaptability, and inadequate transmission of cultural symbols in the digital generation of traditional patterns, this paper proposes a textile pattern generation system based on deep learning and image processing. Methodologically, the input image quality is first improved through preprocessing, and data standardization is achieved through denoising, histogram equalization, and normalization. A convolutional neural network with a residual structure is then used to extract geometric and color features. A conditional generative adversarial network is introduced in the generation phase, optimizing pattern quality and style consistency through adversarial training using a U-Net-structured generator and a convolutional discriminator. In post-generation processing, an adaptive style transfer algorithm is used to jointly optimize content loss, style loss, and edge preservation loss to achieve dynamic adjustment of color, texture, and line. Finally, a super-resolution convolutional neural network is used to reconstruct the pattern, enhancing the resolution while ensuring stable output of detail and color. This work develops a complete technical pathway at the system level from image acquisition, to feature extraction, to pattern generation, to high-resolution optimization that also provides a scalable solution for modern digital expression of traditional patterns.

METHODS

Data Preprocessing and Pattern Feature Extraction

In the preprocessing stage of the data workflow outlined in Section “METHOD”, the first step taken on the collected traditional Chinese pattern images was to remove noise. For all images, a median filter algorithm was used to eliminate salt-and-pepper noise and a Gaussian filter was used to smooth the images, thereby reducing noise prior to the subsequent feature extraction for each image. Filtering was followed by increasing the contrast through a contrast adjustment. The contrast adjustment involved using histogram equalization to increase the contrast level to make more details visible in the pattern for future processing steps. A normalization for the image data range to compress to the scaled range [0, 1] followed the contrast-adjustment process, to contain similar pixel values across images for a neutral scale of comparable images as inputs into the neural network, specifically when differences in image brightness may interfere with stability of feature extraction.

After image preprocessing, a convolutional neural network, in the form of a deep learning neural network, was used to extract features from the preprocessed images. CNN extract local image features with a multi-layered convolutional architecture whereby the low-level features such as edges and corners are mapped to high-level features describing the semantics of the image. Most convolutional layers in the

ResNet-50 backbone employ 3×3 kernels within bottleneck blocks, while 1×1 convolutions are used for channel reduction and expansion. The study used the ResNet deep learning network architecture for feature extraction. Feature extraction was performed using the ResNet-50 model. This particular network is composed of residual connections configured in 50 layers. The network activation function is ReLU, and the residual connection is held together by a convolutional layer that begins its channels with 64 in the first layer, then continues the channel configuration with additional channels of 128, 256, and 512 in consecutive layers up to the end of this stage. Meanwhile, a global average pooling layer produces a 2048-dimensional feature vector from the final convolutional layer. Residual connections were utilized to solve the vanishing gradient problem during the training stage of deep networks and to stabilize the training of networks in processing complex patterns. Moreover, a color feature extraction module was also implemented to increase the capability to extract both color and texture features of the pattern. The extraction module transforms the displayed image into the YUV color space, which decouples the brightness and color information of the pattern, while improving recognition of the color distribution and the details of the texture present in the screen displayed to the user. Color spaces are selected based on characteristics required for the specific processing. The YUV space separates luminance and chrominance to help identify features. The HSV color space is modeled on approximations of perceptual representation of color distribution. The Lab space enables accurate color manipulations, independent of the output devices. Each transformation adds its own computational cost, but each transformation has its specific benefits for its purpose. The color feature extraction module was affixed to input after the output of the 2nd residual stage of the ResNet-50 model architecture. The input image was transformed to YUV color space, separating the luminance component from the chrominance components. A dedicated convolutional layer downstream of the YUV color transformation processed the U and V chrominance channels, which had 64 filters of size 1×1. Output from this layer was combined with the feature maps from the main ResNet pathway. Downstream of the concatenation layer, there was a fusion convolutional layer with 256 filters of size 1×1 which integrated the concatenated features ensuring uniform dimension along the main network flow. The feature extraction is illustrated in Figure 1.

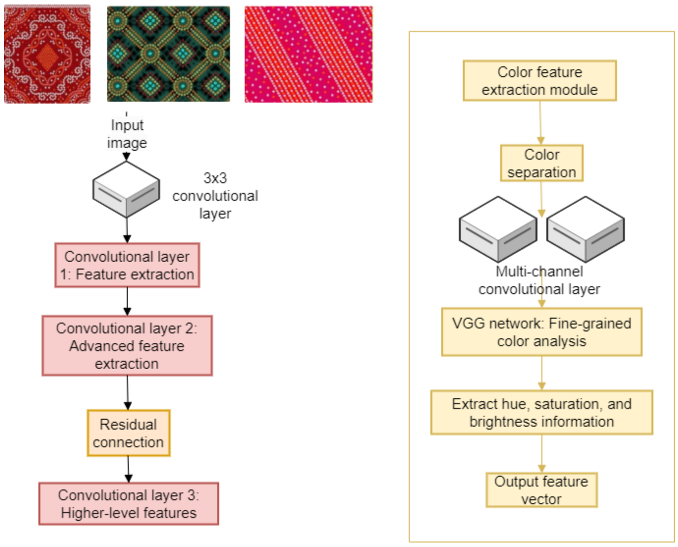

Figure 1. Feature Extraction

Figure 1 displays a deep learning architecture that combines a convolutional neural network with a color feature extraction module for pattern style analysis. The left branch employs a ResNet structure for the extraction of geometric features, and the right branch has a VGG (Visual Geometry Group Network)-based network as an independent color sub-network for extracting style vectors for color analysis. The network consists of several residual blocks, each containing a series of layers of convolutions and identity shortcut connections, allowing the residual characteristics to mitigate the vanishing gradient problem in training deep networks and maintaining the stability of network training to process complex patterns. The VGG network analyzes color distribution through the retention of extracted hue, saturation, and brightness from multi-channel layers of convolutions to analyze the color distribution. The high-level features are combined through fully connected layers to output a vector that retains the geometric, color, and texture characteristics of the pattern [17,18].

Pattern Generation and Optimization

In accordance with the feature extraction process, the pattern generation process utilizes a conditional generative adversarial network to produce patterns corresponding to traditional styles. In the model's generator, the task of generating each pattern begins by receiving pattern feature vectors produced by a convolutional neural network, as well as conditional information associated with the style a pattern generator is to follow in the generation process, such as geometry, color distribution, and texture details.

The conditional information is formed based on the semantic analysis and quantification of cultural symbols analyzed within the traditional patterns. Geometric elements and plant and animal themes are categorized as discrete cultural symbol categories and encoded using one-hot encoding. Pattern color distribution is quantified through a computational process that analyzes the main color histogram of the input image within the HSV color space, which is normalized as part of the pre-processing step. Texture detail characteristics are defined computationally by analyzing the grayscale co-occurrence matrix of the image and calculating numerical statistics of its energy and contrast in pixels. Following the encoding of information the scalars are spliced together into a multidimensional conditional vector. Each feature component within the conditional vector is normalized to a common numerical scale using min-max normalization. The contribution of different conditional components to the output is assessed, and features with negligible impact on generation quality are excluded to maintain a compact representation. At the input of the generator, the conditional vector is spliced together with the pattern feature vector extracted by the convolutional neural network as the joint input of the generator itself. This concatenated one-dimensional vector is first projected and reshaped into a two-dimensional feature map with an initial spatial dimension through a fully connected layer. The generator consists of a U-Net architecture that includes skip connections which improves the generator's ability to retain detail when generating patterns. The U-Net encoder consists of four stages of down-sampling with 3x3 convolution kernels. The first stage contains 64 feature maps, and each stage doubles the number of feature maps. The decoder also features four upsampling stages with 3x3 convolution kernels and halves the number of feature maps at each stage. There are skip connections between layers of the encoder and decoder to preserve spatial integrity. The convolutional layers of the generator extract features from the images, while the upsampling layers incrementally reconstruct the spatial resolution of the image through deconvolution. As the generator generates the image, its task is to generate a quality pattern that is visually coherent to the traditional pattern style. The discriminator assesses whether the pattern generated by the generator is real or not. The discriminator has a network architecture that is again based on a convolutional architecture, taking as input both the generated pattern from the generator and a real traditional pattern.

During the training stage of cGAN (Conditional Generative Adversarial Network), the generator and discriminator learn from each other by adversarial training. The generator's objective is primarily to optimize the quality and style congruence of the generated patterns and thus generate patterns that are increasingly similar to the target style; the discriminator's goal is to improve its accuracy of judgment when distinguishing the generated patterns from real patterns. The training is structured around an alternating optimization scheme: the discriminator's weight parameters are set first while the generator is trained to produce patterns that are increasingly similar to real patterns; The generator and discriminator are alternately optimized in an iterative manner during training. The overall cGAN training process is illustrated in Figure 2.

Figure 2 shows how the conditional generative adversarial network trained, demonstrating the adversarial loss for the generator and discriminator across training iterations. The generator loss decreased because the generator was learning to create patterns that approximated the real distribution. The discriminator loss exhibits fluctuations as a result of the adversarial balance between the generator and discriminator. It is this adversarial process that leads to high quality patterns that retain cultural features and conform to contemporary design practices.

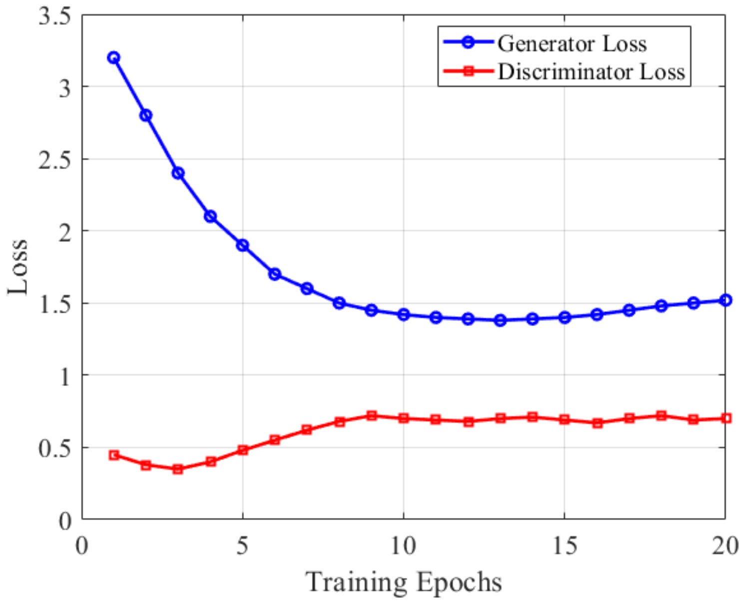

Figure 2. Adversarial Training

Style Transfer and Visual Expression Adjustment

After generating the pattern, an adaptive style transfer algorithm optimizes the visual characteristics of the generated pattern. The algorithm effectively adapts color matching, line orientation, and texturing of the generated pattern [19,20]. The process starts with a convolutional neural network-based model for style transfer by amalgamating the stylistic features of the generated pattern with the target traditional pattern. The model takes the style images from the generated pattern and the target traditional pattern as input. The aim is to relaborate the visual characteristics of the generated pattern to reflect the complete artistic style of the target while maintaining the content structure. The loss functions include content loss and style loss.

The content loss reconstructs the content portion of the image, and it checks for the preservation of the structure of the original pattern by calculating the distance between the generated pattern and the original content image. Assuming the target content image is I_c and the generated pattern is I_g, their outputs in a certain layer of convolutional feature map are Φ_c and Φ_g, the content loss $L_{content}$ is calculated as:

$$L_{content}=\frac{1}{2}\sum_{i,j}\left(\Phi_c(i,j)-\Phi_g(i,j)\right)^2 \tag{1}$$

In formula (1), $\Phi(i,j)$ is the feature value at position (i,j) in the feature map, ensuring that the structure of the generated pattern is consistent with the target pattern.

The style loss measures the difference in style characteristics between the generated pattern and the target style image. The style is represented by the statistical characteristics of the image. If the target style image is I_s and the generated pattern is I_g, the style loss L_{style} is defined as:

$$L_{style}=\sum_{l} w_l \cdot \left(\|G_l(I_g)-G_l(I_s)\|^2\right) \tag{2}$$

In formula (2), $G_l(I)$ represents the Gram matrix of image I at layer l, w_l is the weight of this layer, $G_l(I)$ is calculated using $A_l^T A_l$, and A_l is the feature map of layer l.

Next, an adaptive style transfer algorithm is used to further tune the visual effect of the pattern. Adaptive style transfer differs from the traditional implementation of style transfer because it will adaptively personalize the intensity of the style transfer depending on the characteristics of the input image and will best personalize the color, line art, and texture. The algorithm introduces an adaptive factor, $\alpha(l,t)$, to adjust the weight of the style loss w_l at each layer:

$$w_l^{new}=w_l \cdot \alpha(l) \tag{3}$$

In formula (3), $\alpha(l)$ automatically adjusts based on the different features of the input image, enabling the strength of style transfer to be adjusted at different training stages and image characteristics. The adaptive factor $\alpha(l)$ is calculated based on the statistical properties of the feature map A_l of the input image I_g at layer l. The feature map A_l has dimensions C × H × W. The factor $\alpha(l)$ sums the squared Frobenius norm of A_l with its per-channel variance. This sum is normalized to the range [0, 1] via linear scaling using the feature statistics. This calculation relies on the activation strength of the feature map, enabling a flexible modification of the style loss weight based on the image content.

During style transfer, the optimization procedure of the resultant pattern's is to minimize the total loss function, which is a combination of content loss, style loss and edge preservation loss:

$$L_{total}=\lambda_{content} \cdot L_{content}+\lambda_{style} \cdot L_{style}+\lambda_{edge} \cdot L_{edge} \tag{4}$$

Here, $L_{content}$ is the content loss, L_{style} is the style loss, L_{edge} is the edge preservation loss, and $\lambda_{content}$,λ_{style},λ_{edge} are weighted hyperparameters for each loss term. The hyperparameters $\lambda_{content}$,λ_{style}, and λ_{edge} were set to 1, 100, and 10 respectively. These values were determined through empirical tuning on a validation set to balance the contributions of content preservation, style transfer, and edge enhancement. The edge preservation loss term L_{edge} is defined to optimize the clarity and structural integrity of pattern contours. The loss calculates the L2 norm of the difference between the generated pattern and target content image Laplacian response. The Laplacian operator is chosen because it accentuates the second-order spatial derivatives, thus increasing the sharpness of pattern edges and fine structural details in the pattern, while maintaining edge retention in the Laplacian response compared to the original pattern, and preventing excessive edge distortion or blurring during training. The Laplacian operator is applied to both images to enhance edges and lines.

Lastly, the hue adjustment module produces an affine transformation to optimize the pattern's color combination to produce the intended outcome for various textiles and to meet production specifications.

As a result of the hue adjustment in Lab color space, the hue of the pattern is optimized along a color gradient with adjusting saturation, allowing the color of the pattern to produce the intended visual outcome on varied materials or textiles [21,22].

High-Resolution Pattern Generation and Enhancement

First, the generated pattern is downscaled to a low resolution. This simulates the generated pattern at low resolution for input to super-resolution reconstruction. The super-resolution reconstruction process restores high-frequency details and detail accuracy in the image using the Super-Resolution Convolutional Neural Networks. SRCNN is an end-to-end deep learning model that takes low-resolution images as input and generates high-resolution images as output. SRCNN is a three-layer convolutional neural network. The first layer extracts the low-resolution image preliminary features through convolution. The second layer refines image features and performs feature mapping. Finally, the final high-resolution output image is generated in the third layer. The super-resolution process nominally uses a 2× upscaling factor. This results in a low-resolution input image has a pixel dimension of 128×128 pixels, which results in a high-resolution output image of 256×256 pixels. SRCNN performs single-stage super-resolution reconstruction. This pixel dimension serves as the digital resolution to prepare the generated pattern. The SRCNN network structure is shown in Table 1.

Table 1. SRCNN Network Structure

Convolutional layers	Feature map size	Feature extraction functions
1	33x33	Extracting low-level features
2	31x31	Feature refinement
3	29x29	Restoration of high-frequency details

Table 1 outlines both the roles served by each of the three convolutional layers of the SRCNN model, alongside the dimensions of their output feature maps, and their extracted features. SRCNN first upsamples the low-resolution image using bicubic interpolation. The upsampled image is then processed through the convolutional layers to reconstruct high-resolution details. The learned hierarchy of features allows SRCNN to learn to recover details in low-resolution images, and particularly subtle textures and edges.

During the training process, SRCNN minimizes mean squared error (MSE) loss function to optimize the parameters of the network by minimizing the pixel-wise difference between the reconstructed image and the target high-resolution image. Through repeated cycles of training, the network learns how to extract even more details from the low-resolution image. This includes fine-line and complex texture details within the pattern that further improve image clarity. At the final output of the pattern, color correction techniques are implemented to adjust the color to meet the color style of the original pattern, preventing distortion of the enhanced image detail and deviation from original color style. The colors are adjusted to correspond with the vision of the overall pattern while improving resolution, while meeting the color requirements to modern textiles.

EXPERIMENTAL EVALUATION

The experiment utilized an image dataset of traditional Chinese patterns divided into the categories of geometry, flowers, and animals. The dataset includes a total of 15,000 authorized images with balanced class distribution, such that there are 5,000 images per class. A stratified random sampling strategy was used to ensure that the proportion of images in each class is maintained across the training and test datasets. The images were split so that the training dataset contained 80% of the images while the test dataset had 20%. Feature extraction is completed using a convolutional neural network (CNN) and a conditional generative adversarial network (CGAN) is trained to generate patterns. A discriminator is trained to allow for verification of patterns with adversarial training, which improves quality. An adaptive style transfer algorithm is used to optimize the colors, lines, and textures of patterns being generated to modern design, while a super-resolution algorithm is used to optimize resolution for production in textiles. Quality of the image patterns is measured by comparing the experimental group (using the proposed method) with the control (using traditional methods) based on pattern quality, detail accuracy, and cultural symbol representation. The Adam optimizer was applied while training the model with a learning rate of 0.001. A learning rate scheduling strategy also halved the learning rate every 20 training epochs. The training batch size was 32, and the total number of training epochs was 100. Experiments were conducted on a hardware platform equipped with an NVIDIA Tesla V100 GPU. Inference latency was measured using the same hardware configuration and utilizing a single image, which measured an average inference time of 50 ms.

Pattern Generation Quality

In this study, we investigated the evolution of performant generative models in image reconstruction tasks, in order to evaluate their capabilities to sufficiently express image structure and detail while learning. We investigated generative adversarial networks (GANs), autoregressive generative models (ARMs), variational autoencoders (VAE), and the deep learning model developed in this paper. The GAN was used in the form of an adaptation of a deep convolutional GAN with five million parameters. The ARM utilized the PixelCNN architecture, which consisted of four million parameters. The VAE uses a standard architecture with three million parameters. Each comparison model utilized the same training dataset, which was randomly sub-sampled into a training and a test set, using a training test split of 80:20%, with the same number of training epochs of one hundred. The ML model was specified to have six million parameters and the same training terms as the comparison models. We recorded the structure similarity metric (SSIM) and the peak signal-to-noise ratio (PSNR) from each model, in each successive training round, so we could evaluate and analyze results. By visualizing the results generated from each training round we were able to observe the trends of the model extracting image features, and converging during learning, thus visually demonstrating performance differences of the various methods during training, as shown in Figure 3.

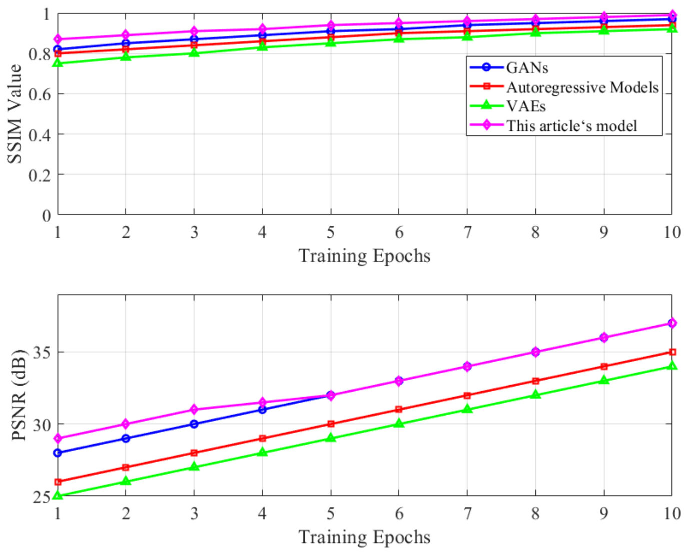

Figure 3. Pattern Generation Quality

As can be observed in Figure 3, our model exhibits high SSIM and PSNR growth rates at the beginning of training, followed by a steady upward trend as the number of training rounds increases. The SSIM and PSNR growth of GAN in the early stages of training is slightly faster than those of VAEs and autoregressive models, but the growth rate slows in the middle and late stages, which may be due to the fluctuation of generated features caused by the instability of adversarial training. The indicators of the autoregressive model gradually increase, indicating that it has a continuity advantage in capturing local pixel dependencies, but is slightly insufficient in preserving global structure. The performance of VAEs is limited by the constraints of the latent space and the smoothness of the reconstruction loss, resulting in relatively weak detail recovery capabilities. The steady growth of our model is due to the design of the network structure and the optimization of the loss function, which balances feature extraction with global consistency, thereby maintaining a continuously improving performance level as the number of training rounds increases, ultimately demonstrating superior reconstruction results.

The model's exceptionally high SSIM and PSNR values reflect its ability to achieve near-perfect structural and perceptual alignment with reference patterns, thanks to comprehensive feature learning and optimization within a deep learning framework. The conditional generative adversarial network integrates multiple levels of constraints, including geometric structure, color distribution, and texture detail, enabling accurate reconstruction of pattern elements. The adversarial training process ensures that the generated patterns maintain high fidelity without directly replicating the training examples, as evidenced by the diversity of cultural symbolic representations and detailed differences in the output. The generated patterns achieve a structural similarity index of 0.99 and a peak signal-to-noise ratio of 37 dB. These values confirm the model's high capability in structural preservation and perceptual quality. Evaluation on an independent test set confirms that these metrics stem from generalized pattern synthesis rather than overfitting. The model's design incorporates adaptive mechanisms to strike a balance between fidelity and novelty, supporting its reported performance on complex image generation tasks.

Image Detail Accuracy

To evaluate the generative model's robustness in detail restoration at different spatial locations, a local accuracy analysis experiment based on gradient strength and structural similarity was conducted. The generated image was divided into a regular grid, and the edge gradient magnitude and local structural similarity mean were calculated for each cell, reflecting line sharpness and texture consistency, respectively. These two metrics were linearly normalized and merged into a detail accuracy matrix, which was then displayed as a color map to visualize its spatial distribution. This visualization method, based on regional statistics, allows for observation of differences in the model's detail restoration across different regions, revealing the spatial accuracy characteristics of the generation process. The mean local structural similarity is calculated using the structural similarity index, with a window size of 11 pixels and a sliding step of 1 pixel. Calculate the magnitude of the Laplace response using the Laplace operator. The Laplacian difference is defined as an approximation of the second derivative of each pixel in the image, achieved through convolution with a standard Laplacian kernel. The Laplacian kernel is a 3x3 matrix with a center value of -4, adjacent values of 1, and the rest of the values being zero. The absolute value of the convolution kernel with the image is used as the Laplacian response magnitude. The results are shown in Figure 4.

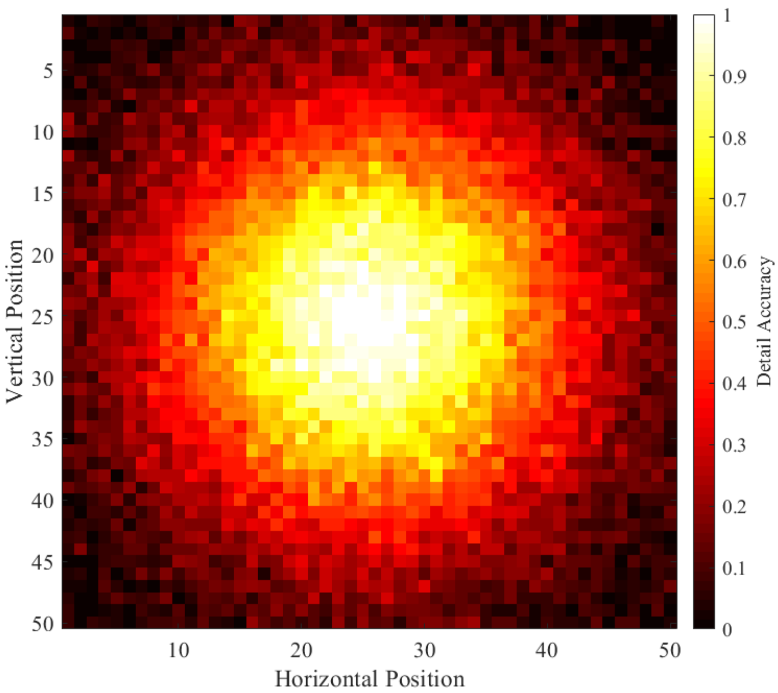

Figure 4. Spatial Distribution of Detail Accuracy Heatmap

Figure 4 shows that the image center exhibits higher detail accuracy, while the edge regions exhibit slightly lower values. This distribution is related to the generative model's feature response mechanism. The model's convolutional receptive field is concentrated in the center, resulting in higher feature aggregation and shorter gradient propagation paths, leading to better preservation of detail information in the center. At the edge, due to reduced effective convolution kernel coverage, feature fusion is limited, and high-frequency information of local structure is partially attenuated during the generation and reconstruction stages, resulting in reduced detail accuracy. The overall distribution shows that the model's detail response in spatial distribution has a center-first characteristic, showing the law of local fidelity variation caused by differences in feature aggregation intensity.

Cultural Symbol Representation

Each model's generated pattern was evaluated using cultural element recognition to quantify the preservation of cultural symbols such as plants, animals, and geometric shapes. Artificial intelligence algorithms identified cultural elements within the pattern, and image analysis techniques were used to calculate the representation of each symbol. Scoring criteria were based on the symbol's clarity, accuracy, and alignment with traditional cultural elements. The recognition accuracy of each generated model's pattern on each type of cultural symbol was quantitatively scored on a scale of 0 to 100. Cultural symbol recognition accuracy is defined as the proportion of generated patterns that are correctly classified into their target cultural symbol categories. A pre-trained image classification model is employed for this evaluation. The model architecture is a convolutional neural network based on ResNet-50, trained on the annotated dataset of traditional patterns used in this study. The model performs multi-class classification across plant, animal, and geometric shape categories. For each generated pattern, the target cultural symbol category is derived from the conditional information provided during the generation process. The recognition accuracy for each symbol type is calculated as the number of patterns correctly classified as that type divided by the total number of patterns generated for that type, multiplied by 100. The formula for the accuracy Acc for a symbol type c is $Acc\_c = (N_{correct} / N_{total}) * 100$, where $N_{correct}$ represents the count of patterns correctly classified as type c, and N_{total} represents the total number of patterns generated for type c. Figure 5 shows the performance of each model on different cultural symbols.

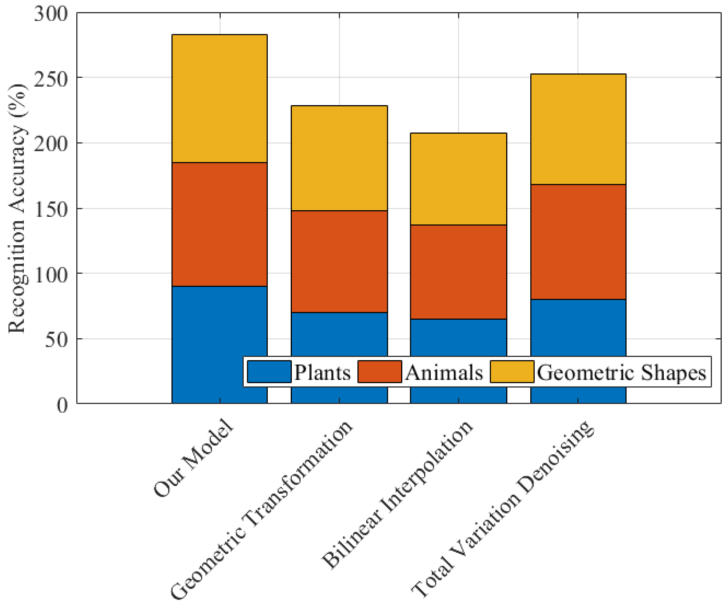

Figure 5. Cultural Symbol Recognition Accuracy

Figure 5 shows the performance of different algorithms in terms of cultural symbol communication. The horizontal axis represents proposed model, the geometric transformation algorithm, the bilinear interpolation algorithm, and the total variation denoising algorithm. The vertical axis shows the recognition accuracy of each cultural symbol (plant, animal, geometric shape) using each algorithm. Proposed model achieved a plant symbol recognition accuracy of 90, significantly higher than the other algorithms (the geometric transformation algorithm scored 70, the bilinear interpolation algorithm scored 65, and the total variation denoising algorithm scored 80). Proposed model achieved an animal symbol recognition accuracy of 95, the highest among all algorithms. Other algorithms scored relatively low, including 78 for the geometric transformation algorithm, 72 for bilinear interpolation, and 88 for total variation denoising. Proposed model also achieved a recognition accuracy of 98 for geometric shape symbols, outperforming other algorithms (80 for the geometric transformation algorithm, 70 for bilinear interpolation, and 85 for total variation denoising).

Resolution and Clarity

This article sets the initial image resolution and clarity index as a pre-training baseline. Model training begins with multiple training rounds. In each round, the model continuously optimizes parameters based on the training data and generates new images. At the end of each training round, the corresponding pattern is generated and its resolution and clarity index are calculated. The Clarity index is defined as the output variance of the generated image after processing with the Laplacian operator. The Laplacian operator uses a standard 3x3 kernel with a center value of -4 and neighboring values of 1. The variance is calculated based on the processed image matrix, reflecting the sharpness of edges and details. This index assesses visual sharpness by quantifying the intensity of high-frequency components in the image.

In Figure 6, the horizontal axis represents the number of training epochs, the left vertical axis represents the image pixel size, and the right vertical axis represents the sharpness index. The initially generated image pixel size was 256×256 pixels, and after training, the final pixel size increased to 320×320 pixels. In the first few training epochs, the sharpness was low, between 0.75 and 0.80. In the 4th to 7th training epochs, the sharpness gradually improved, rising from 0.80 to 0.89. After 8 to 10 training epochs, the pattern sharpness significantly improved to 0.95, indicating that the training process significantly optimized the pattern details.

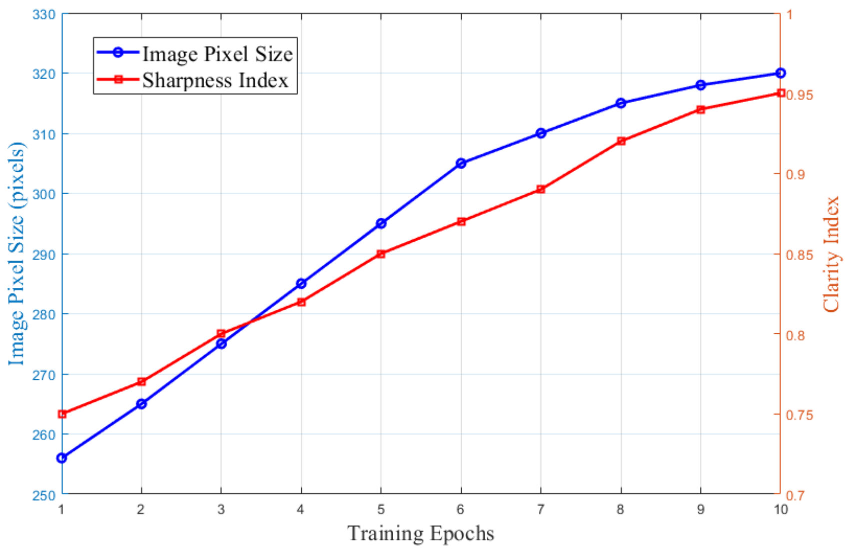

Figure 6. Resolution and Clarity

CONCLUSION

This paper proposes a digital textile pattern generation system using deep learning, combining a convolutional neural network (CNN), conditional GAN (cGAN), and super-resolution (SRCNN) to improve design efficiency and quality. The CNN captures key geometric and color features of traditional Chinese patterns, while the cGAN optimizes the generation process to maintain cultural style. A style transfer algorithm and visual adjustment techniques enhance artistic expression, and SRCNN boosts resolution for high-quality output. The system significantly reduces production time—generating patterns in seconds, compared to hours or days with manual methods—while preserving precision and cultural fidelity. Batch processing capabilities further support modern textile workflows focused on speed and quality.

Author Contributions

Chenxing Zhang designed, collected and analyzed the data, and drafted the manuscript. Chenxing Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Chenxing Zhang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The author declares no conflict of interest.

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