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Realization of Transfer Learning-based Chinese Character Calligraphy Style Transformation Technique in Transnational Cultural Communication

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SUMMARY: *As an important carrier of Chinese culture, Chinese calligraphy has unique value in transnational cultural communication.In this research paper, we develop a Chinese character calligraphy generation system to implement the application of Chinese character calligraphy style transfer technology in cross - national cultural communication. After conducting in - depth research on style transfer technology and CycleGAN, we build a Chinese character calligraphy generation model named CRA - GAN. This model is aimed at enhancing the quality of generated Chinese character calligraphy. Subsequently, a Chinese character calligraphy generation system is designed to boost the cross - national cultural dissemination of Chinese character calligraphy. The CRA - GAN model designed in this paper shows excellent performance in the task of converting the style of Chinese character calligraphy, and the model has high values of SSIM, FSIM, PSNR and low values of RMSE, and the mean value of subjective evaluation of the generated Chinese characters by professionals is mostly 8 or 9 points. It was verified by linear regression that after the application of the Chinese character calligraphy generation system, the attitudes of expatriates towards Chinese character culture were significantly improved, and the realization of the Chinese character calligraphy style migration technology is of great significance for transnational cultural communication.*

KEYWORDS: *style migration; CycleGAN; CRA-GAN; Chinese character calligraphy generation system; linear regression; transnational cultural communication*

1 Introduction

Chinese characters have been the basic tool for ideological and cultural exchanges among Chinese nationalities since their creation. In the process of long-term communication and use, scholars of various nationalities in successive generations have continuously created and transformed the form and structure according to the needs of communication, as a result, they have steadily developed from oracle bone inscriptions and bronze inscriptions to the Great Seal Script, the Lesser Seal Script, the Clerical Script, the Grass Script, the Standard Script, and the Semi - cursive Script. t [1, 2]. Relying on the hieroglyphic symbols of Chinese characters, they further abstracted the lines and structures of Chinese characters, and at the same time incorporated their own life sentiments and aesthetic experiences to create a unique art in the world - Chinese character calligraphy. Chinese character calligraphy is not only an outstanding

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traditional Chinese culture, but also an important means and tool of communication among the Chinese people. Preserving and advancing Chinese character calligraphy is advantageous for "defining and emphasizing the emblems of Chinese culture and the collective image of the Chinese nation embraced by all ethnic groups, and strengthening the cultural identification of all ethnic groups with Chinese culture". Moreover, it contributes to the cultivation of a sense of community among the Chinese nation [3-5].

Chinese calligraphy is a kind of profound Chinese culture, and the wide dissemination of Chinese culture in the global scope can make other countries and regions of the world know and understand China better, expand China's influence, and is a good way to change the “stereotypical impression” of China in some countries [6]. At present, the transnational dissemination of calligraphy through academic exchanges, cultural exchanges, online media, its high threshold and cultural differences, resulting in the majority of people concerned about the professionals. A piece of literature [7] selects the “Tang - style calligraphy” from the Edo era in China as its subject matter. The aim is to delve into the amalgamation and development of calligraphy within the context of cross - cultural communication. This exploration occurs under the constraints of international exchange, Tang-style calligraphy absorbed Chinese calligraphic techniques through direct and indirect paths and recreated them locally, reflecting the dual dynamics of selective absorption and creative interpretation in cultural transmission. Literature [8] proposes a framework for the international dissemination of Chinese calligraphy based on the theory of empathic communication, emphasizing that through the three dimensions of emotional contagion, transpositional thinking and empathic care, and with the help of strategies such as narrative reconstruction, multimedia display and interactive experience, we can overcome the barriers of linguistic and philosophical cognition, so as to establish an emotional connection and cultural identity, and thus to realize the effective dissemination of calligraphy and cultural dialogue in the world.

As one of the important methods of calligraphy inheritance and development, style transfer has become an important path for disseminating calligraphy. Literature [9] uses Generative Adversarial Network (GAN) to realize the automatic transfer of calligraphy styles, and through the synergy of the dual networks of content supplementation and style transfer, it transforms the standard fonts into the styles of specific famous artists, effectively reduces the manual intervention, and provides a new idea for the development of fonts. Literature [10] This study proposes a multi-task model that combines convolutional neural network and GAN to realize calligraphy style migration and automatic generation using conditional GAN, which outperforms the mainstream methods in terms of structural fidelity, stylistic performance and perceptual consistency. Although GAN is a commonly used style transfer technique, there still exists the case of stroke breakage after the conversion. Transfer learning, in which knowledge learned from one environment is used to help learning tasks in a new environment, raises new perspectives for transnational dissemination of Chinese calligraphy. Literature [11] combines the transfer learning of denoising method of deep convolutional neural network with connected region technique, which specifically targets the noise and scratches in Chinese flat calligraphy images, effectively removing the noise and preserving the details of the text structure. Literature [12] utilizes a migration learning method for style determination and alphabet classification of Arabic calligraphy, which serves as a key step in image-to-text, automates the interpretation of historical documents, and provides an effective technological path for the digital understanding of cultural heritage.

The study utilizes the style migration technique and recurrent generative adversarial network to design a contour- and region-aware attention-based method (CRA-GAN) for generating Chinese calligraphy characters. The generated calligraphic characters are objectively evaluated in terms of four metrics, namely SSIM, FSIM, PSNR, and RMSE, respectively, and subjectively evaluated in terms of five dimensions, namely, structural accuracy, stroke restoration, contour clarity, style matching, and visual aesthetics. After verifying that the model is able to accomplish the task of calligraphic style conversion, the technology is applied to construct a Chinese character calligraphy generation system. We counted the attitudes of foreigners after experiencing the system, and used regression analysis to verify the effectiveness of the system on the transnational cultural communication of Chinese calligraphy.

2 Chinese Character Calligraphy Generation Based on Transfer Learning

2.1 Technical principles

2.1.1 Style migration techniques

Style migration refers to migrating the style of graph A to graph B, i.e., generating a graph C with the style of graph A and the content of graph B. A white noise image is trained based on the content and style maps to obtain a style migrated image. Text font style migration is performed by inputting content reference samples and style reference samples into the style migration network, and the generated fonts then have both the content of the content samples and the style of the style samples.

2.1.2 Generating Adversarial Networks

The objective of generative adversarial networks aligns with that of generative models. for a random distribution of input generators, the network has to generate outputs that fit the distribution of real data. Before the emergence of generative adversarial networks, one of the major difficulties of generative models was how to determine whether the network outputs fit the real data or not, and generative adversarial networks proposed to use another neural network to make the judgment, which is the discriminator. The generator is responsible for generating the input random noise to fit the output of the real data, The discriminator's role is to assess whether the output is suitable, the two play with each other, and eventually make the whole network into the Nash equilibrium state. Let the model input be z, the real data be x, $p_{data}(x)$ be the real probability distribution function, $p_z(z)$ be the generated probability distribution function, and the optimization objective of the whole model is:

$$\begin{aligned}\min_G \max_D V(G,D) = E_{x\sim p_{data}(x)}\left[\log D(x)\right] \\ +E_{z\sim p_z(z)}\left[\log(1-D(G(z)))\right]\end{aligned} \tag{1}$$

Equation (1) illustrates the principle of GAN, where the task of the generator G is to make its output $G(z)$ fit the real data distribution as well as possible, “fooling” the discriminator, which corresponds to making the value of equation (1) as small as possible. The discriminator D, on the other hand, has the opposite task, which is to make Eq. (1) as large as possible by distinguishing the true from the false. The two networks are trained at the same time, i.e., they are co-evolving, and their respective outputs provide guidance for the training of the other network, which grows against each other and eventually reaches a Nash equilibrium.

Figure 1 depicts the fundamental structure of the Generative Adversarial Network (GAN).

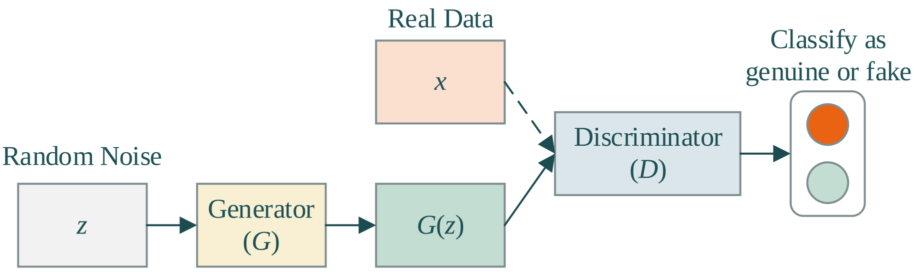


Figure 1: Gan's basic framework

2.1.3 Cyclic generative adversarial networks

Unlike GAN, CycleGAN contains 2 generators and 2 discriminators.The basic network framework of CycleGAN model is shown in Fig. 2.In order to make up for the lack of feature constraints caused by insufficient pairwise data, CycleGAN model introduces a symmetric mapping from target domain to source domain on top of the original mapping from source domain to target domain.

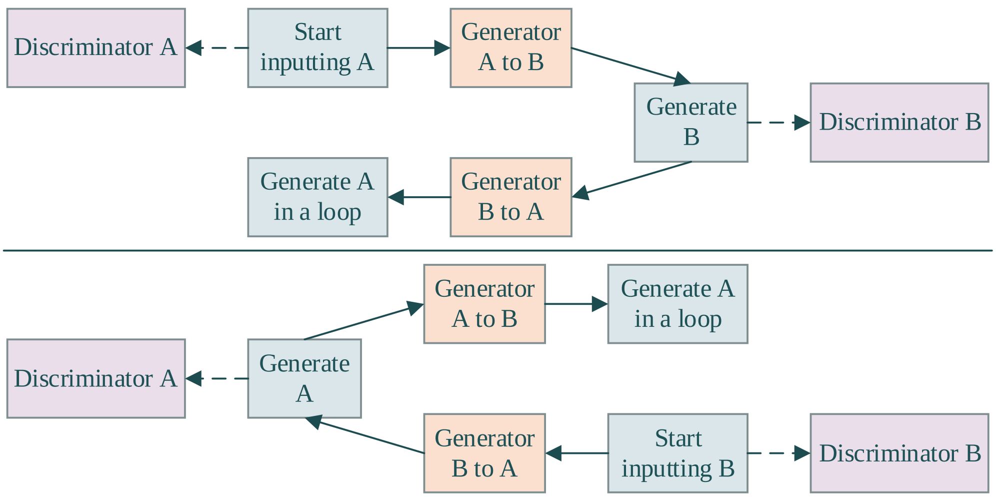


Figure 2: CycleGAN model basic network framework

Figure 3 depicts the internal architecture of the CycleGAN model network. If the model employs just a single generator and discriminator, during the training process, it will transform all Chinese - character images into one of the character images from the famous calligraphy font images. This is done to obtain higher scores. However, this approach significantly strays from the original objective of the Chinese - character generation task. Therefore, it is essential to utilize two sets of generator - discriminators to impose constraints, enabling the model to better accomplish the generation task.

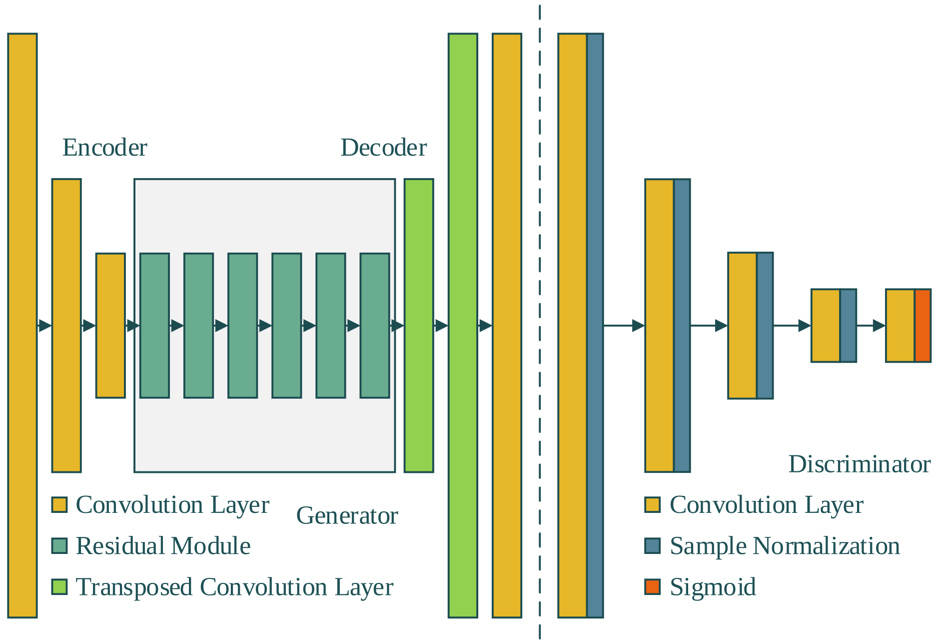


Figure 3: CycleGAN model network internal structure

2.2 Design of Chinese Character Calligraphy Generation Method Based on Transfer Learning

In this research paper, we put forward a technique for creating Chinese calligraphy characters. This method, named Contour and Region - Aware Attention - based Chinese Calligraphy Generation (CRA - GAN), employs CycleGAN as the fundamental network. To enhance the quality of calligraphy character generation, we incorporate contour details, region - sensitive attention mechanisms, and adaptive pre - morphing strategies. .

2.2.1 Model structure

Figure 4 depicts the general framework of the CRA - GAN approach. In this method, CycleGAN serves as the fundamental network. Specifically, it comprises an adaptive pre - deformation unit (AP), a calligraphy contour extraction unit (CE), two region - sensitive attention generators, and two discriminators, where we use the same discriminators as in CycleGAN.

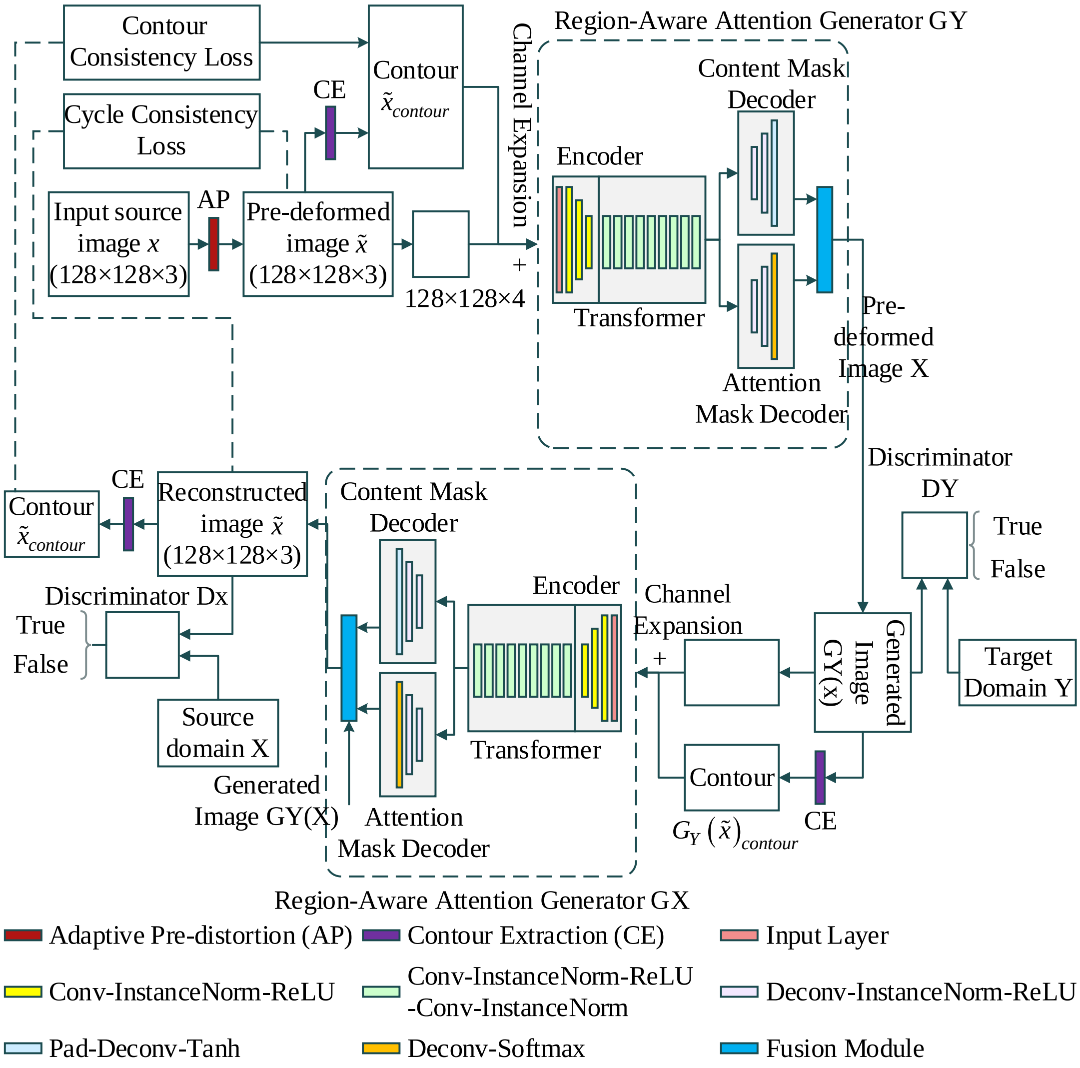


Figure 4: CRA-GAN model structure

The task of this paper is to generate calligraphic characters based on unpaired datasets, i.e., to learn the mapping between the source domain X and the target domain Y, i.e., $G_Y : X \to Y$ and $G_X : Y \to X$. The specific workflow of the CRA-GAN method proposed in this paper is as follows: given a Chinese character image x from the source font domain, the predeformed image $\tilde{x}$ is first generated by the AP module, and then the contour of $\tilde{x}$ is extracted by the CE module, and then the RGB three-channel Chinese character image $\tilde{x}_{contour}$ is subsequently expanded by the channel expansion method. channel Chinese character image $\tilde{x}$ and its extracted single-channel contour image $\tilde{x}_{contour}$ are then fused into a four-channel representation by channel expansion. The four-channel representation is then fed into the region-aware attention generator G_Y to generate the calligraphic character image $G_Y(\tilde{x})$ in the target domain. At the same time, on the one hand, the generated calligraphic word image $G_Y(\tilde{x})$ is input to the discriminator D_Y for D_Y to discriminate the truth from the falsehood, and on the other hand, $G_Y(\tilde{x})$ is passed through the CE module, and then $G_Y(\tilde{x})$ and its contour image $G_Y(\tilde{x})_{contour}$ are The fusion input is fed into another region-aware attentional generator G_X to generate the reconstructed image $\hat{x}$, a discriminator D_X to discriminate between the truth and falsity of $\hat{x}$, and extracts the contour of $\hat{x}$ as a kind of pseudo-label to be used to compute the contour consistency loss in order to constrain the model. Similarly, another mapping $G_X : Y \to X$ is done. The next three subsections describe the implementation details of the three specific modules in detail.

2.2.2 Adaptive Pre-deformation

An adaptive pre-morphing module enables the source and target fonts to remain essentially aligned on the overall font area, thus reducing the font glyph differences, which in turn allows the network to better learn the mapping between the source and target domains, and to more accurately learn the internal features of the Chinese characters. The specific procedure of the adaptive preformation module (AP) is as follows:

Step 1: Given a Chinese character x_i in the source font dataset X of size N_X, the maximum outer join matrix of the image of size $128*128$, i.e., the Chinese character region, is first calculated by the edge detection algorithm, and then the height (h_x) and width (w_x) of this Chinese character region are recorded, and the average literal face occupancy ratio (avg_crp_X) and the average height-to-width ratio (avg_hwr_X) based on the source Chinese character image set X can be computed by the following equation:

$$avg\_crp_X = \frac{1}{N_X}\sum_{i=1}^{N_X}\frac{h_x * w_x}{128*128} \tag{2}$$

$$avg\_hwr_X = \frac{1}{N_X}\sum_{i=1}^{N_X}\frac{h_x}{w_x} \tag{3}$$

Similarly, we can derive the corresponding average literal face occupancy ratio (avg_crp_Y) and average aspect ratio (avg_hwr_Y) for the target font dataset Y of size N_Y as follows:

$$avg\_crp_Y = \frac{1}{N_Y}\sum_{j=1}^{N_Y}\frac{h_y * w_y}{128*128}$$

$$avg\_hwr_Y = \frac{1}{N_Y}\sum_{j=1}^{N_Y}\frac{h_y}{w_y}$$

where h_y and w_y denote the height and width of the Chinese character region of y_j in the target font dataset Y, respectively.

Step 2: Using the above four statistical values, adaptive pre-morphing is realized according to the following three cases:

a) If $avg\_crp_X > avg\_crp_Y$, the $resize()$ function is first used to shrink the aspect ratio of each x_i to make it consistent with avg_hwr_Y, and then the white background is filled in to make the image size $128*128$.

b) If $avg\_crp_X < avg\_crp_Y$, zoom each image x_i according to avg_hwr_Y, then crop the image to make the image size $128*128$.

c) If $avg\_crp_X = avg\_crp_Y$, i.e., keep the image itself without adaptive pre-morphing.

Step 3: According to the above four statistical formulas, the pre-morphing operation can be performed on each input source Chinese character image so that the source image is roughly aligned with the Chinese character region of the corresponding target calligraphy image.

2.2.3 Contour extraction

In this research paper, we employ the straightforward and effective Roberts operator to extract the outlines of Chinese character images. Specifically, the Roberts operator leverages the disparity between two adjacent pixels in the diagonal direction to estimate the gradient magnitude for edge detection, and it makes use of the operator template. The formula for calculating the difference is presented as follows:

$$\Delta f_x(x,y) = f(x,y) - f(x+1,y+1) \tag{6}$$

$$\Delta f_y(x,y) = f(x+1,y) - f(x,y+1) \tag{7}$$

The magnitude of its gradient is computed as:

$$F(x,y) = \left[\left(\Delta f_x(x,y)\right)^2 + \left(\Delta f_y(x,y)\right)^2\right]^{\frac{1}{2}} \tag{8}$$

Therefore, the threshold T is appropriately chosen such that a pixel (x,y) is considered as an edge point if $F(x,y) > T$.

2.2.4 Area-aware attention generator

The region - sensitive attention generator adheres to the encoder - decoder framework. It is composed of a parameter - sharing encoder, a converter, a content mask decoder, an attention mask decoder, and a fusion module. The parameter - sharing encoder processes the four - channel input image to generate a feature depiction. A converter, which is formed by nine residual blocks arranged in a stack, transforms the feature representation of the source font domain into that of the target font domain. The content mask decoder is inclined to detect the foreground content of the Chinese character. Meanwhile, the attention mask decoder has a tendency to capture both the foreground content area and the background area. It is designed to fuse the foreground content mask $\left(\{C_y^f\}_{j=1}^{n-1}\right)$, the foreground content region attention mask $\left(\{A_y^f\}_{j=1}^{n-1}\right)$ and the background region attention mask (A_y^b) as well as the input characters x in the source font domain to obtain the calligraphic character region and the background region of the calligraphic character image, Subsequently, these are combined to create the desired calligraphic character $G_Y(x)$. Here, n represents the quantity of masks employed in the model. In the actual implementation of the proposed model, we adopt the default $n = 10$ value of . The mathematical expression is presented as follow:

$$G_Y(x)=\sum_{j=1}^{n-1}\left(C_y^f\otimes A_y^f\right)+x\otimes A_y^b \tag{9}$$

where $\otimes$ denotes pixel-level cumulative multiplication.

Likewise, when an image y is input, the output image $G_X(y)$ generated G_X by the generator can be expressed as:

$$G_X(y)=\sum_{j=1}^{n-1}\left(C_x^f\otimes A_x^f\right)+y\otimes A_x^b \tag{10}$$

2.2.5 Design of the loss function

The process of training the model integrates adversarial loss, cyclic consistency loss, and contour consistency loss. For the mapping $G_Y:X\rightarrow Y$, G_Y generates the calligraphic image $G_Y(\tilde{x})$ that looks as similar as possible to the image in the domain Y, while D_Y distinguishes between the real y and the generated $G_Y(\tilde{x})$ as much as possible, and the other mapping $G_X:Y\rightarrow X$ does the same thing, Consequently, the adversarial loss can be formulated as :

$$\begin{aligned}L_{adv}\left(G_X,G_Y,D_X,D_Y\right)=&E_{y\sim p_Y(y)}\left[\log D_Y(y)\right]\\&+E_{\tilde{x}\sim p_X(\tilde{x})}\left[\log\left(1-D_Y\left(G_Y(\tilde{x})\right)\right)\right]\\&+E_{\tilde{x}\sim p_X(\tilde{x})}\left[\log D_X(\tilde{x})\right]\\&+E_{y\sim p_Y(y)}\left[\log\left(1-D_X(\hat{x})\right)\right]\end{aligned} \tag{11}$$

where G_Y, G_X aim to minimize the adversarial loss, while D_Y, D_X maximize it as much as possible.

Considering that the content of the reconstructed image and the real original image should be consistent, i.e., $G_X(G_Y(\tilde{x}))\approx\tilde{x}$, and $G_Y(G_X(y))\approx y$, the content is bounded by the L_1 loss:

$$\begin{aligned}L_{cyc}\left(G_X,G_Y\right)=&E_{\tilde{x}\sim p_X(\tilde{x})}\left[\left\|G_X\left(G_Y(\tilde{x})\right)-\tilde{x}\right\|_1\right]\\&+E_{y\sim p_Y(y)}\left[\left\|G_Y\left(G_X(y)\right)-y\right\|_1\right]\end{aligned} \tag{12}$$

where $G_X(G_Y(\tilde{x}))$ and $G_Y(G_X(y))$ are reconstructed images, and $\|\cdot\|_1$ denotes L_1 paradigm.

Once the calligraphic outlines are extracted from the Chinese character images, a significant quantity of superfluous data is eliminated. Meanwhile, the essential structural details of the strokes are also emphasized. Thus, we propose the contour consistency loss $L_{contour}(G_X,G_Y)$ to ensure the contour consistency between $G_X(G_Y(\tilde{x}))$ and $\tilde{x}$, $G_Y(G_X(y))$ and y. $L_{contour}(G_X,G_Y)$ can be expressed as:

$$L_{contour}\left(G_X, G_Y\right) = E_{\tilde{x}\sim p_X(\tilde{x})}\left[\left\| CE\left(G_X\left(G_Y(\tilde{x})\right)\right) - CE(\tilde{x})\right\|_1\right] + E_{y\sim p_Y(y)}\left[\left\| CE\left(G_Y\left(G_X(y)\right)\right) - CE(y)\right\|_1\right] \tag{13}$$

Here, CE stands for the contour extraction procedure, which serves to extract the outlines of both the reconstructed image and the original Chinese character image. Ultimately, our overall loss function is defined as:

$$L_{CRA-GAN}\left(G_X, G_Y, D_X, D_Y\right) = L_{adv}\left(G_X, G_Y, D_X, D_Y\right) + \lambda_1 L_{cyc}\left(G_X, G_Y\right) + \lambda_2 L_{contour}\left(G_X, G_Y\right) \tag{14}$$

where λ_1, λ_2 are the weights of each loss.

2.3 Analysis of the effect of Chinese character calligraphy style conversion

2.3.1 Experimental data

In this paper, we mainly use the data of 7 common style fonts in Chinese calligraphy, which contain Regular Script, Running Script, Cursive Script, Official Script, Seal Script, Weibei, and Slim Gold Script. The 500 characters in the standard character set GB2312 were selected for the data set of these 7 fonts respectively. The fonts were downloaded from the official websites of the corresponding font manufacturers in ttf or otf format, and pre-processed into 256px×256px RGB images with black characters on a white background by Python code, which constituted the paired training datasets of seven groups of 500 characters,These fonts will serve as the source and target fonts in the model's comparison experiments, aiming to verify the model's capacity for style migration, respectively. And 30 characters were randomly selected from the GB2312 character set other than these 500 characters as the training test set to verify the inference generation ability of the model. After this step, all the datasets have been converted into binary image format containing information about the structure, shape and features of Chinese characters, which significantly reduces the computational burden of the model training process.

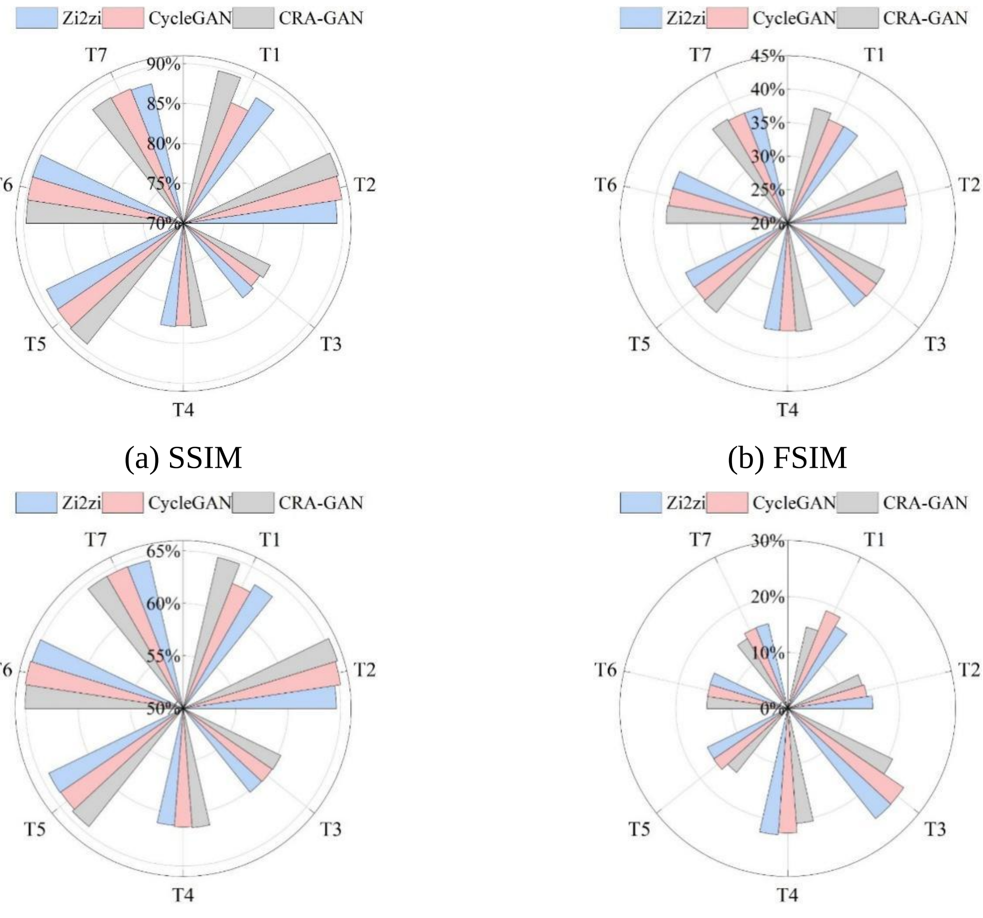
2.3.2 Objective assessment

In this research paper, for the objective evaluation experiments, image similarity metrics are employed to assess the similarity indicators between the font image produced by CRA - GAN and the target font image, as well as between the font image generated by the comparison model and the target font image. To guarantee the objectivity and dependability of the outcomes, four image similarity measurement evaluation criteria are selected in this study. These criteria are: SSIM (structural similarity index), FSIM (feature - based similarity index), PSNR (peak signal - to - noise ratio), and RMSE (root - mean - square error). SSIM is a measurement used to gauge the resemblance of two images, taking into account three elements: luminance, contrast, and structure.The advantage is that SSIM's perceived sensitivity to brightness, contrast and structure makes it more compatible with the human visual system. FSIM is an image similarity metric that combines local contrast, global contrast and structural information. PSNR on the other hand is a metric that measures the quality of an image by comparing the RMSE (root mean square error) between the original image and the compressed generated image. The RMSE metric is the square root of the squared mean of the difference between the observed value and the true value, which is a simple, intuitive and easy-to-calculate metric. Higher magnitudes of the

Structural Similarity Index Measure (SSIM), Feature Similarity Index Measure (FSIM), and Peak Signal - to - Noise Ratio (PSNR) signify that the image produced by the model exhibits a greater level of resemblance to the target image, and smaller values of RMSE indicate that the model-generated image has less discrepancy and a higher degree of similarity with the target image.

The experiment set up seven groups of Chinese character calligraphy style conversion tasks: The transitions include from running script to regular script (T1), from running script to seal script (T2), from running script to thin gold style (T3), from regular script to cursive script (T4), from regular script to clerical script (T5), from seal script to running script (T6), and from cursive script to Weibi (T7).

Comparing CRA-GAN with two mainstream models, Zi2zi and CycleGAN, respectively, the statistics of similarity indices of Chinese character generated images are shown in Fig. 5, and (a)~(d) denote the statistics of SSIM, FSIM, PSNR, and RMSE indexes, respectively. After the experiments and the analysis and statistics of the experimental data, the model proposed in this paper obtains better image similarity measurements compared to the comparison model in seven different groups of calligraphic style conversion tasks. Among the seven groups of results CRA-GAN obtains larger values for SSIM, FSIM, PSNR metrics and smaller values for RMSE metrics on at least six groups of experimental data, which more objectively proves that the effectiveness of this paper's model for character outline edge optimization and the ability of font style migration under 500-character samples.



(a) SSIM (b) FSIM

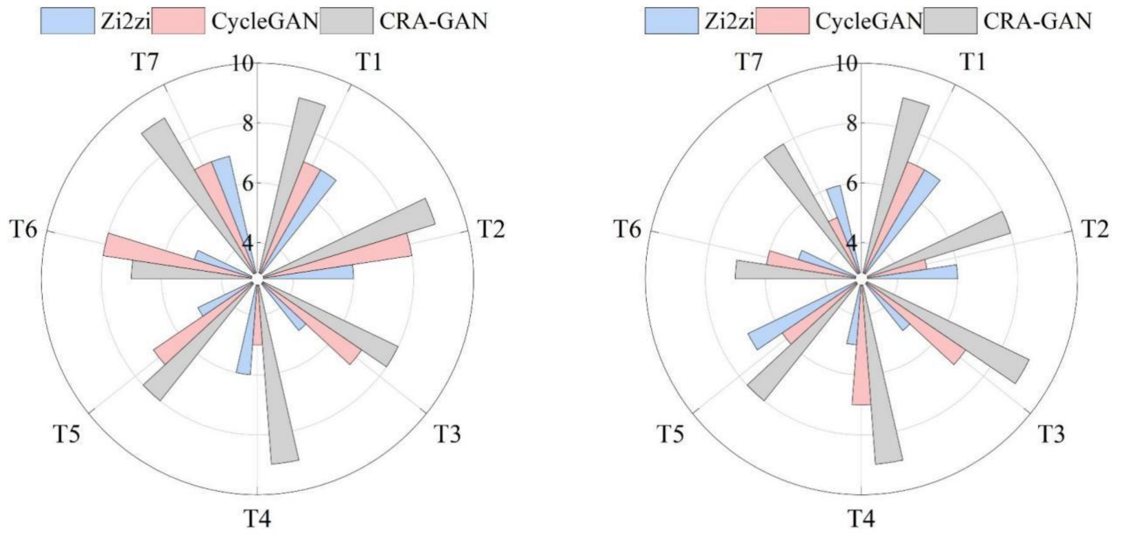
(c) PSNR (d) RMSE

Figure 5: Chinese characters generate image similarity index statistics

2.3.3 Subjective assessment

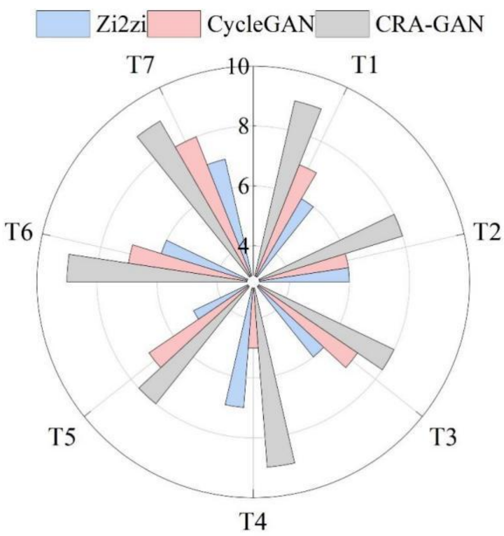
To conduct a comprehensive evaluation of the quality of the character images produced by the three models, we designed a questionnaire and invited 30 professionals with in-depth knowledge of Chinese calligraphy styles to participate in the scoring. The questionnaire contains five scoring options, namely: structural accuracy, stroke reproduction, outline clarity, style matching, and visual aesthetics. The score of each option is set from 1 to 10 points without setting decimal point. After careful observation and analysis of the effects of the seven groups of Chinese character images generated, It has been discovered that the Chinese character images produced by the CRA - GAN model exhibit notable benefits across every metric. In particular, the Chinese character images created by CRA - GAN possess more distinct outlines, finer stroke reproduction, and more rigorous structural features.

Thirty professionals made subjective judgments based on their own aesthetics and experience on seven sets of character images generated by the three models with different styles. The findings regarding the similarity scores of the images produced by the Chinese characters are presented in a summarized form, as depicted in Figure 6, with (a)~(e) indicating the scores of structural accuracy, stroke reduction, outline clarity, style matching, and visual aesthetics, respectively. The images produced by the model presented in this paper outperform those of the comparison model across all five metrics, with average scores predominantly ranging from 8 to 9. The strengths of this paper's model are manifested not only in the sharpness of contours and the fidelity of stroke reproduction but also in the precision of structure, the harmony of style, and the visual appeal of the generated characters. Collectively, the advantages in these areas contribute to the overall competitiveness of this paper's model within the domain of font generation.

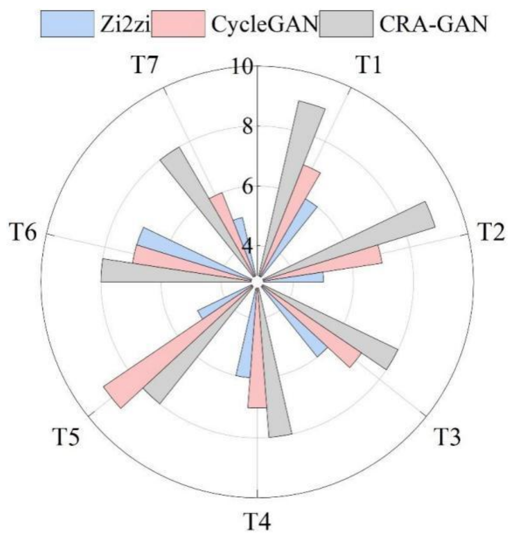


(a) Structural accuracy

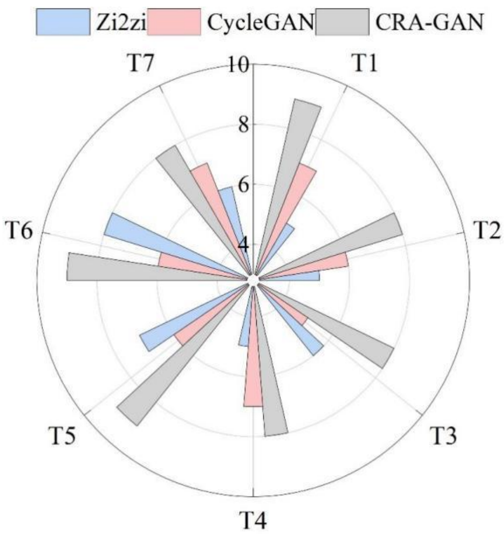
(b) Brush reduction



(c) Contour resolution



(d) Style matching



(e) Visual vision

Figure 6: The results of the image similarity score of Chinese characters

3 The Impact of Chinese Character Calligraphy Generation System on Transnational Cultural Communication

3.1 System design

In this paper, we set out to design a handwriting editing system with good user interactivity and calligraphy generation function. Calligraphy generation function is to be able to real-time calligraphy rendering of the user's input handwriting, handwriting editing function is to the handwritten input calligraphy fonts for scaling, arranging, inserting, deleting, modifying and other operations. Handwriting editing is different from ordinary text input, handwriting editing input and display in the same interface, so it must deal with layer management and user interaction. The functions of this system are as follows:

(1) Calligraphy generation function. Users can write on the touch screen in real time on the handwriting calligraphy simulation, showing a certain calligraphy effect.

(2) Editing function. As a handwritten notepad supports common editing operations, including insertion, deletion, carriage return, space, cursor positioning, expression and so on.

(3) Personalization. Including page style, background pattern, font size, character spacing, paragraph spacing, stroke size, landscaping style, color and so on.

(4) Data storage and file management. It mainly stores, loads and deletes handwriting data and pictures, including file format and coding definition, data storage and file management.

(5) Terminal Adaptation. The same experience can be obtained on devices with different resolutions, mainly including calligraphy generation parameters and display interface terminal adaptation.

This system employs the MVC design paradigm. In this context, M represents the logical model, V stands for the view model, and C denotes the controller. The objective of implementing the MVC pattern is to achieve the segregation of the logical model from the view interface. As a result, the same program can be utilized in diverse modes of presentation. Android system provides a good similar environment for realizing the classic MVC design pattern. The basic framework of this system is shown in Figure 7, which is an MVC structure consisting of a user view interface, a document data model, and a control center. The user view mainly includes the display interface and user interaction, and makes corresponding changes when the document data model changes. The document data model includes data unit definitions, such as page model, calligraphy font parameter model, and other attributes. The control center receives requests from the interface, changes the document data units through the corresponding logical interface, and then responds to the requests accordingly.

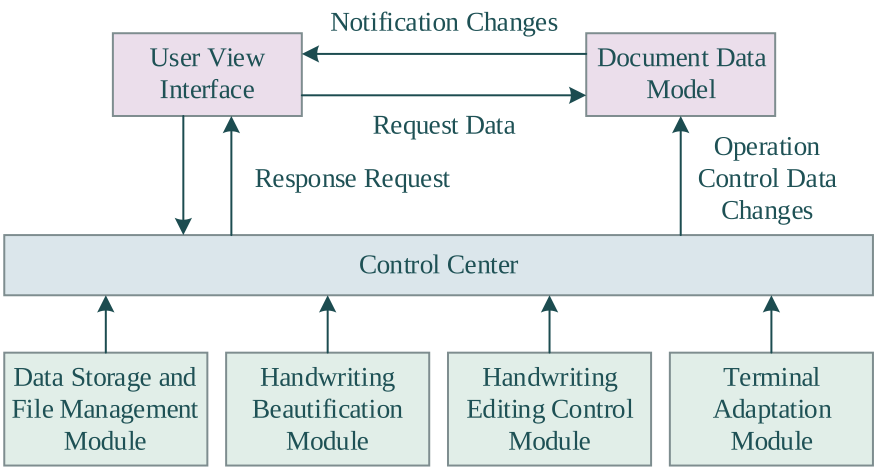


Figure 7: Chinese character calligraphy generation system

3.2 Analysis of the impact of system applications on transnational cultural communication

3.2.1 Research design

In this study, we chose the expatriate community in China as the research object, and conducted the research from March 2025 to July 2025 in three more representative cities, Shanghai, Beijing, and Guangzhou. A questionnaire was distributed to 500 expatriates who had experienced the Chinese character calligraphy generation system to explore expatriates' cultural attitudes toward calligraphy in terms of two dimensions: cultural commonality and perceived value (D7), where cultural commonality includes shared language (D1), shared values (D2), and awareness of calligraphy culture (D3), and perceived value includes social value (D4), cultural value (D5), and sense of cultural belonging (D6), and the questionnaire was designed with five dimensions: social value (D4), cultural value (D5), and sense of cultural belonging (D6), and the questionnaire was designed with five dimensions. (D6), and the questionnaire was designed to investigate with a 5-point Likert scale. Due to unavoidable reasons, a total of 450 questionnaires were finally recovered, and after screening and checking the validity of the recovered questionnaires, 434 valid questionnaires were finally obtained, and the effective recovery rate of this questionnaire research was 86.8%.

3.2.2 Descriptive statistics

The results of the experience evaluation of the Chinese character calligraphy generation system by expatriates in China are shown in Table 1. The survey results show that the 434 expatriates in China who experienced the Chinese character calligraphy generation system were more agreeable to the shared language (D1), shared values (D2), social values (D4), cultural values (D5), and sense of cultural belonging (D6) of Chinese character calligraphy, and that the system was able to enhance the expatriates' cognition of the culture of calligraphy (D3) and their attitudes toward the culture of calligraphy (D7), with the mean ratings of three points The mean value of the scores are all above 3 points.

Table 1: The evaluation results of the Chinese character calligraphy generation system

Variable	Mean	SD	Min	Max	Sample
D1	3.21	0.216	1	5	434
D2	3.22	0.237	1	5	434
D3	3.44	0.285	1	5	434
D4	3.22	0.243	1	5	434
D5	3.14	0.262	1	5	434
D6	3.56	0.281	1	5	434
D7	3.88	0.117	1	5	434

3.2.3 Correlation analysis

Person correlation analysis was used to explore the relationship between shared language, shared values, cultural perception of calligraphy, social values, cultural values, cultural belonging, and cultural attitudes towards calligraphy variables. The results of the correlation analysis are shown in Figure 8. The correlation coefficients between the variables ranged from 0.348 to 0.707, all of which were significantly positive (P<0.001).

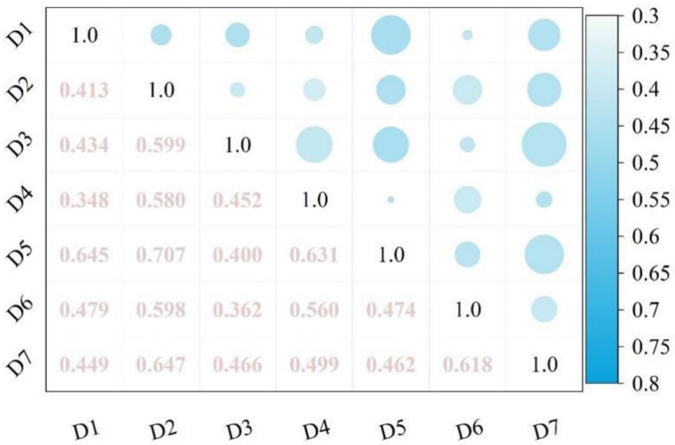


Figure 8: Correlation analysis results

3.2.4 Regression analysis

Based on the outcomes of the correlation examination, it can be seen that there are more correlations between the variables, and further hierarchical regression analysis was conducted to further explore the relationship between these variables after controlling for the demographic variables. The results of the linear regression of the expatriates' evaluation of their experience with the Chinese character calligraphy generation system are shown in Table 2. In the demographic model, a significant positive effect of length of time in China was found (β=0.036, p<0.01). In the dependent variable model, shared language (β=0.124, p<0.05) and shared values (β=0.118, p<0.01) were found to have a positive effect on cultural attitudes toward calligraphy, i.e., cultural commonality has a positive effect on cultural attitudes toward calligraphy. Cultural value (β=0.091, p<0.05), social value (β=0.255, p<0.001) and cultural belonging (β=0.614, p<0.001) have a positive effect on cultural attitudes toward calligraphy, i.e., perceived value has a positive effect on cultural attitudes toward calligraphy.

Table 2: Linear regression of system experience evaluation

Predictor variable	Model 1	Model 2
Demography		
Gender	0.051 (0.055)	0.036 (0.041)
Age	0.085 (0.055)	0.036 (0.052)
The length of time in China	0.036** (0.041)	0.166** (0.026)
Familiarity with Chinese	-0.011 (0.041)	0.059 (0.038)
Familiarity with Chinese calligraphy	0.263*** (0.044)	-0.006 (0.035)
Cultural commonality		
D1	-	0.124* (0.036)
D2	-	0.118** (0.046)
D3	-	0.037 (0.028)
Perceived value		
D4	-	0.091* (0.034)
D5	-	0.255*** (0.036)
D6	-	0.614*** (0.025)
Adjust R^2	7.22%	69.85%
ΔR^2	7.9%***	60.5%***
Sig.	0.000	0.000

Note: *p<.05, **p<.01, ***p<.001, Model 1 is the control variable model and Model 2 is the independent variable model. Values are standardized regression coefficients β, and standard error of scale S.E. is in parentheses.

The findings of the regression analysis indicated that the experiential encounter of the Chinese character calligraphy generation system had a positive effect on the expatriates' attitudes toward calligraphy culture, with those who had resided in China for a longer period of time having better attitudes toward calligraphy culture.

4 Conclusion

In this research paper, we developed a system for generating Chinese character calligraphy. This system makes use of the Chinese character calligraphy style conversion method founded on transfer learning, and explored the attitudes of expatriates towards calligraphy culture after experiencing the Chinese character calligraphy generation system based on regression analysis. The following conclusions are drawn from the empirical analysis:

(1) The Chinese character calligraphy generation model (CRA-GAN) designed in this paper has higher values of SSIM, FSIM, and PSNR than the two mainstream models with Zi2zi and CycleGAN, and lower values of RMSE than the comparison models. Most of the assessment mean values of structural accuracy, stroke reproduction, outline clarity, style matching and visual aesthetics of the Chinese characters generated by the model in this paper are 8 or 9 points, and the subjective evaluation results also have significant advantages.

(2) After experiencing the Hanzi Calligraphy Generation System, foreigners had a positive influence on the cultural attitude toward calligraphy in terms of both cultural commonality and perceived value. Through linear regression, it is verified that the Chinese character calligraphy generation system designed based on the Chinese character calligraphy style conversion technology is favorable to the transnational dissemination of calligraphy culture.

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