Deep Learning Based Oracle Style Migration and Generation Techniques

Yingjie Qiao, Lizhi Xing

Abstract—**This paper introduces a deep learning-based oracle style migration and generation technique, whose core capability lies in converting arbitrary modern Chinese characters into characters with oracle features. This paper proposes a StyleGAN-based oracle style migration and generation model, which utilizes a GAN framework of style encoder, image reconstructor, and multidiscriminator, thus realizing the generation of high-quality, high-resolution, diverse, and realistic oracle images. This paper also provides an in-depth evaluation of this paper's model in terms of multiple dimensions and key metrics, including style migration effect, style generation effect, generation efficiency and expert evaluation, and compares it with other comparative models to demonstrate the superiority and innovation of this paper's model. This paper provides an effective and innovative solution to solve the problem of recognizing and understanding ancient texts.**

Index Terms—**deep learning, oracle, style migration, style generation**

I. Introduction

As one of the earliest writing systems in China, Oracle Bone Script carries a wealth of historical records, myths and legends, and philosophical ideas, and its glyphs are simple but far-reaching, with compact structures and meanings that often rely on contextual interpretation [1,2]. The application of deep learning to the reconstruction of glyphs and innovative generation of oracle bones is a modern technological interpretation of the heritage of ancient civilization. At present, there are some problems in the development of oracle, as shown in Fig. 1. Deep learning-driven image style migration technology shows a wide range of application potential in many fields such as art creation, entertainment design and even medical imaging. The technology mainly realizes the conversion or fusion of image content and style attributes through convolutional neural networks, and can be roughly divided into two categories: methods based on Generative Adversarial Networks (GANs) and technology paths based on neural stylization algorithms (e.g., AdaIN, StyleGAN, etc.) [3]. GAN-based methods play an important role in image style migration, which consists of a generator network and a discriminator network that form a competitive relationship to train the generator to capture target image domain features from random noise, and then create new images with similar or very different styles based on the input content images [4].

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Yingjie Qiao is an associate professor of School of Art and Design, Luoyang University of Science and Technology, Luoyang 471000, China. (e-mail: QiaoYingjie_1@outlook.com).

Lizhi Xing is a Ph.D. student at the Yellow River Civilization and Sustainable Development Research Center of Henan University, Luoyang 471000, China. (co-first author, corresponding author, e-mail: lizhi_xing@outlook.com).

On the other hand, approaches based on neural stylization algorithms focus on digging deeper into the connections between different layers and channels within the convolutional neural network as a way to decompose image content and style information. Using these multi-layer or multi-channel features, style migration can be realized even in sparse, irregular or non-linear scenes [5,6]. The advantages of this approach are low computational complexity, low resource consumption, effective training and fine-tuning even with limited data, and flexible and adjustable migration effects. Focusing on the oracle bone writing domain, the deep learning-based style migration and generation technique aims to draw on the above two image style migration strategies to realize the accurate reproduction or creative synthesis of oracle bone character shapes, constructions, and their connotations, while maintaining the original meanings or endowing them with new cultural meanings [7,8].

The research introduces a groundbreaking Oracle Style Migration and Generation Model, leveraging advanced StyleGAN architecture. This model uniquely combines a style encoder, image reconstructor, and multi-discriminator, enabling the unprecedented generation of high-fidelity, high-resolution oracle bone images. It pioneers a dual-strategy, integrating GAN-based style migration with neural stylization techniques for enhanced contextual interpretation and semantic preservation, addressing the challenges inherent in ancient text understanding. Through rigorous evaluation and comparison, this methodology showcases superior performance, efficiency, and creativity, marking a significant leap forward in deciphering and preserving ancient written heritage.

II. Literature review

Image style migration, as one of the cutting-edge applications of deep learning in the field of computer vision, aims to fuse the content features of the source image with the target style features to create new images with novel artistic expressions. This chapter will systematically explore and summarize the current mainstream image style migration technology approaches and their classifications, including Optimization-based methods, GAN-based methods, CUT-based methods, StyleGAN-based methods, CLIP-based methods, and Diffusion Model-based methods [9].

Style migration originates from the early Neural Style Transfer (NST) algorithm, which centers on extracting the content and style features of an image by means of a Convolutional Neural Network (CNN) and utilizing a loss function to achieve simultaneous style transfer while content is maintained. Specifically, such methods rely on optimization tools such as backpropagation and gradient descent to iteratively update pixel values over the space of the input image to minimize the difference between content and style. Although such methods are theoretically intuitive and fundamental, in practice they often face problems such as unstable training, slow convergence, and limited results, especially when dealing with complex or large-scale style migration tasks [10,11].

Generative Adversarial Networks (GANs) provide new ideas for image style migration. Under this framework, the generator is responsible for generating images with the target style from the potential space, while the discriminator tries to distinguish between the real image and the generated image, and the two promote the effect of style migration through a dynamic game. However, the application of GANs in style migration is not always smooth, such as the pattern collapse problem that may lead to the generation of images with a single style, and overfitting may also limit the model's performance in diversity and detail [12,13].

The CUT approach constructs cross-domain pairs of positive and negative samples and maximizes their differences in corresponding feature representations as a way to guide the style migration process. In order to ensure sufficient feature separation and accuracy of style migration, it is often necessary to design an auxiliary loss function to enhance the learning ability of the model [14].

The StyleGAN family of models revolutionizes the field of image generation and style migration with its outstanding expressiveness, and its specific framework is shown in Fig. 2. Through Adaptive Instance Normalization (AdaIN) and a multi-layer style control mechanism, StyleGAN is able to flexibly manipulate the local and global style attributes of the generated images. However, behind this fine-grained control and high-fidelity generation is a higher demand for computational resources, including a large number of parameters and computations, which somewhat limits its popularity for applications in limited resource environments [15,16].

Image style migration is guided by natural language semantic information in conjunction with the text-image model CLIP (Contrastive Language-Image Pre-training), an approach that allows users to directly manipulate image style changes using natural language cues describing the style, enabling an unprecedented interactive experience. However, this approach relies on a large amount of labeled data to ensure that the model accurately corresponds to linguistic and visual representations, and may be difficult to achieve without sufficient semantic information [17].

In recent years, the diffusion model has gained prominence as an innovative generative model within the realm of image style transfer. This model adeptly mimics the process of gradually refining an image from a state of complete randomness to one of distinct clarity by incrementally reducing noise, thereby achieving high-fidelity image generation and style adaptation. Although the diffusion model demonstrates strong potential in theory, the challenges of gradient computational efficiency and optimization algorithms still need to be addressed in practice to adapt to the demands of real-time and large-scale application scenarios [18].

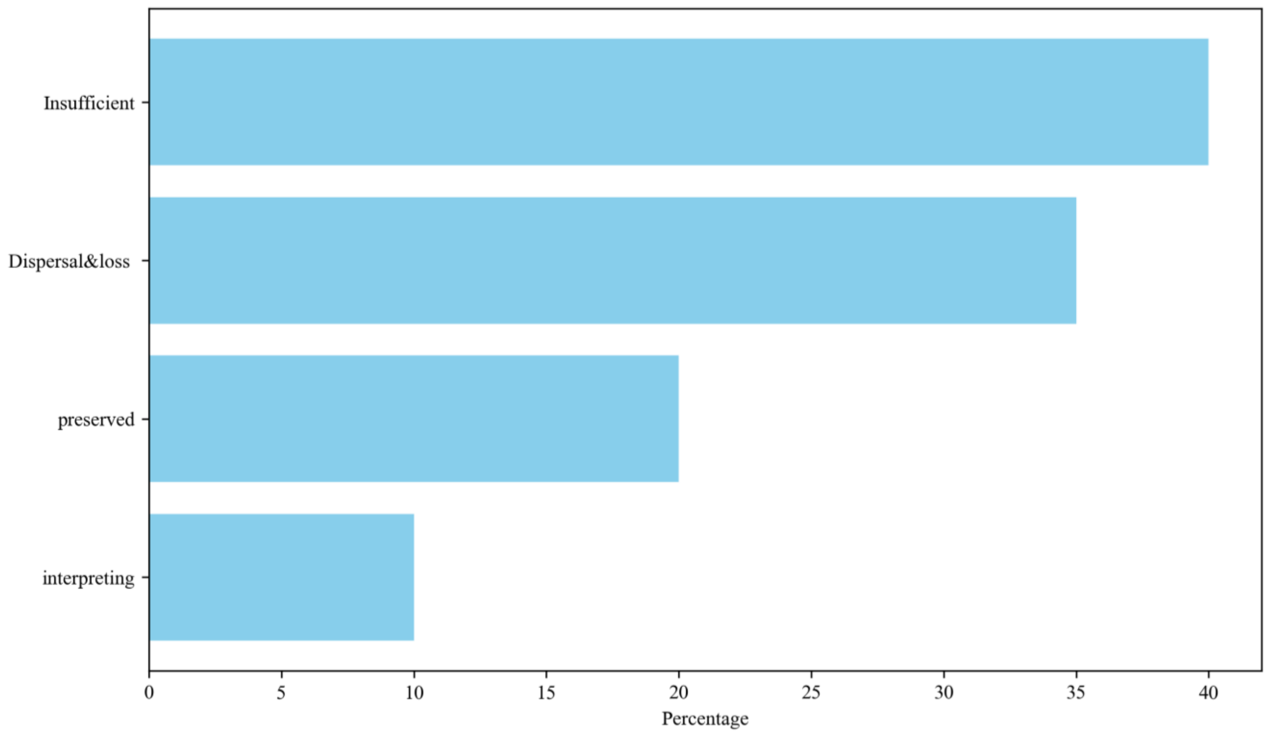

Fig. 1. Problems with Oracle Development

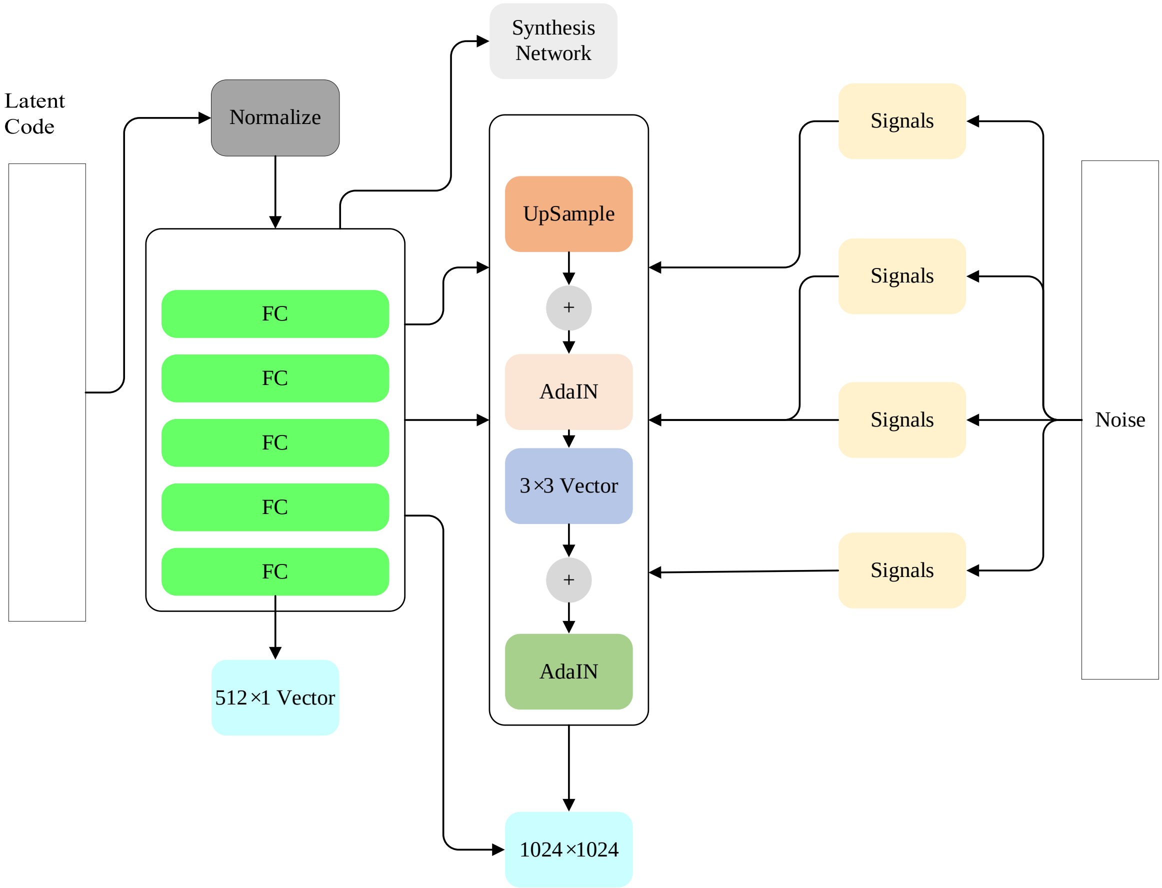

Fig. 2. Framework of StyleGAN

In summary, each style migration method has its own unique advantages and challenges to be overcome, and researchers continue to explore and improve these techniques, aiming to achieve more efficient, stable and diversified image style migration effects, and constantly expand the theoretical boundaries and technical application prospects in this field.

III. StyleGAN-Based Oracle Style Migration and Generative Modeling

A. Model Functions

The StyleGAN based Oracle style migration and generation model proposed in this paper has several features:

(1) Style Migration Function: This function realizes the extraction of content and style information from any kind of modern Chinese characters and converts them into corresponding oracle characters. This function utilizes the synergy of the style encoder and generator, and achieves high-quality style migration effect by performing style transformation in the hidden space [19].

(2) Style Generation Function: This function can realize the automatic creation of new oracle images according to some conditions or inputs. This function utilizes the antagonistic effects of generator and discriminator, and achieves diverse and realistic style generation effects by sampling styles in the hidden space.

(3) Style Reconstruction Function: This function realizes the extraction of structural and detail information from the generated oracle bone image and reconstructs it into an image with the same resolution as the input Chinese characters. This function utilizes the restorative effect of the image reconstructor by performing style reconstruction in the pixel space, thus achieving a clear and realistic style reconstruction effect [20].

B. Principles of StyleGAN

The core idea of StyleGAN is to decompose the image generation process into two stages: style generation and image synthesis. The style generation stage is responsible for extracting style information from the input hidden vector $z \in Z$ and mapping it into an intermediate hidden space $w \in W$. The style generation phase is realized by a mapping network $f: Z \to W$ [21], which is a multilayer fully connected network that converts z into w. w can be viewed as a more decoupled and linear representation of the style, which provides better control over the global and local features of the image. The image synthesis stage is realized by a synthesis network $g: W \to X$ which is a multilayer convolutional network that converts w to the image $x \in X$. Each layer of the synthesis network uses an adaptive instance of the AdaIN layer, which adjusts the scale and offset of the feature maps according to the style information in w. The formula for the AdaIN layer is as follows: $\mathrm{AdaIN}(x_i, y) = y_{s,i}\dfrac{x_i - \mu(x_i)}{\sigma(x_i)} + y_{b,i}$ where x_i is the feature map of the i th channel, $y = (y_s, y_b)$ is the style vector obtained by an affine transformation of w, y_s, i and y_b, i are the scale and offset parameters of the ith channel, μ(xi) and σ(xi) are the mean and standard deviation of the ith channel [22]. The function of AdaIN layer is to align the distribution of the feature map with the style vector so as to realize the effect of style migration [23].

In addition to the AdaIN layer, a noise input is added to each layer of the synthetic network, which adds a random perturbation to the feature maps of each channel to achieve the effect of random changes in the image. The noise input is formulated as follows: $x_i = x_i + \mathrm{N}\ (0,1) \odot \alpha_i$ where xi is the feature map of the i th channel, $N(0,1)$ is a Gaussian noise with the same shape as x_i, $\odot$ is an element-by-element multiplication, and α_i is a learnable weight parameter. The role of the noise input is to increase the diversity and detail of the feature map, thus improving the quality and realism of the image [24].

The generator of StyleGAN can be represented as G=g∘f: Z→X, which consists of a mapping network and a synthesizing network. sty discriminator $D: X \to [0,1]$ is a multilayer convolutional network that determines whether the input image is real or generated. The training objective is $\min_G \max_D \mathrm{E}_{x\sim p_{\text{data}}(x)}[D(x)] - \mathrm{E}_{z\sim p(z)}[D(G(z))]$. Where $pdata(x)$ is the distribution of the real data and p(z) is the distribution of the hidden vectors. In order to ensure that the gradient of the discriminator satisfies the $1-Lipschitz$ constraint, StyleGAN also uses a gradient penalty term, which is formulated as follows: $\lambda \mathrm{E}_{\hat{x}\sim p(\hat{x})}[(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2]$ where x^ is the sample obtained by interpolating between the real and generated data, and λ is a hyperparameter used to balance the adversarial loss and the gradient penalty term [25].

C. Model Improvements

In order to improve the generalization ability of the model, this paper uses a pre-trained StyleGAN model that has been trained on the large-scale face dataset FFHQ1 and is capable of generating high-quality face images. In this paper, the model is used as an initialized generator and then fine-tuned on a dataset containing different Chinese characters so that it can adapt to the style of Chinese characters.

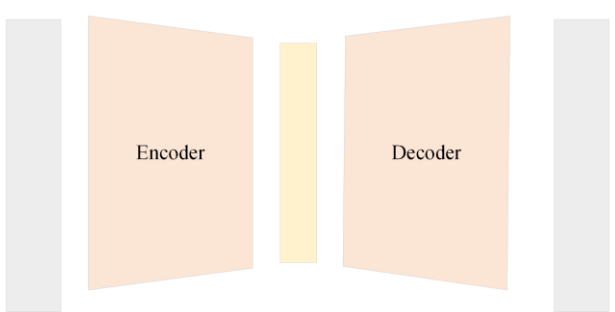

Fig. 3. Style encoder structure

In order to improve the migration capability of the model, a self-encoder based style encoder $E: X \to W$ is used in this paper. The style encoder is shown in Fig. 3. This encoder can extract the content and style information from any kind of modern Chinese characters and encode it into a vector c with the same dimension as the space of w. In this paper, c is used as an input in the image synthesis stage, replacing the original w, which enables the model to generate the corresponding oracle characters based on the input Chinese characters. Specifically, the style encoder in this paper consists of an encoder network $e: X \to C$ and a decoder network $h: C \to X$, where C is an intermediate hidden space with the same dimension as W [26]. The input of the encoder network E is a modern Chinese character image x and the output is a hidden vector c, and the input of the decoder network h is c and the output is a reconstructed image x^. The goal of style encoder E is to make x^ as close to x as possible, i.e., to minimize the reconstruction loss: $L_{\text{rec}} = \mathrm{E}_{x\sim p_{\text{data}}(x)}[\|x - \hat{x}\|_1]$ In this paper, the style encoder shares the weights with the mapping network of the pre-trained StyleGAN model, which results in a bi-directional mapping from x to w, i.e., $E(x) = f-1(x)$ [27]. This ensures that the output c of the style encoder is in the same space as the output w of the mapping network and thus can be used directly for image synthesis.

In order to improve the generation capability of the model, this paper uses an image reconstructor based on a self-attention mechanism $R: X \to X$, which extracts structural and detail information from the generated oracle bone image and reconstructs it into an image with the same resolution as the input Chinese characters. In this paper, the reconstructor is used as an additional discriminator, which, together with the original discriminator, constitutes a multi-discriminator GAN framework, thus enabling the model to generate clearer and more realistic oracle bone images. Specifically, the image reconstructor in this paper is a multilayer convolutional network, in which a self-attention module is added to each layer, which calculates the correlation between different positions in the feature map and performs weighted averaging based on the correlation, thus enhancing the global perception of the feature map [28]. Where x is the feature map, W_Q, W_K, W_V is the learnable weight matrix and dk is the number of channels of the feature map. The role of the self-attention module is to enable the image reconstructor to better preserve the structural and detail information of the generated image, thus improving the quality and realism of the image. The goal of the image reconstructor in this paper is to make the reconstructed image y^ retain the structural and detail information of the generated image y as much as possible, i.e., minimize the perceptual loss: $L_{\text{per}} = \mathrm{E}_{x\sim p_{\text{data}}(x), y\sim p_{\text{model}}(y)}[\|V(x) - V(\hat{y})\|_1]$. Where V is a pre-trained VGG-16 network for extracting high-level features of the image. The role of perceptual loss is to enable the image reconstructor to better capture the semantic similarity between the generated image and the real image, thus improving the realism and coherence of the image [29].

The multi-discriminator GAN framework of this paper consists of a generator G and two discriminators D and R. The goal of generator G is to make the generated oracle image y able to deceive both D and R, i.e., maximize the adversarial loss: $L_{\text{adv}} = \mathrm{E}_{x\sim p_{\text{data}}(x), y\sim p_{\text{model}}(y)}[\log D(x) + \log(1 - D(y)) + \log R(x) + \log(1 - R(y))]$. The goal of the discriminators D and R is to make it possible to distinguish between the real Chinese character image x and the generated oracle image y, i.e., to minimize the adversarial loss $Ladv$. In this paper, the method of $WGAN-GP$ is used, i.e., a gradient penalty term is added to the loss function of the discriminator to ensure that the gradient of the discriminator satisfies the constraints of $1-Lipschitz$, so as to improve the stability and convergence of the model. The overall loss function of the model in this paper is $L = L_{\text{adv}} + \lambda_1 L_{\text{rec}} + \lambda_2 L_{\text{per}}$. Where $\lambda 1$ and $\lambda 2$ are hyperparameters used to balance different loss terms, which are set to 10 and 0.1 in this paper, respectively [30].

D. Model implementation details

In this paper, we use the pre-trained StyleGAN model provided in which configuration F, i.e., using a mixture of regularization and gradient penalties, is used and trained on the FFHQ dataset, which is capable of generating face images with a resolution of 1024 × 1024. The generator G and discriminator D of this model are used as part of the model in this paper, where G includes a mapping network f and a synthesis network g and D is a multilayer convolutional network.

STYLE ENCODER: In this paper, we use a self-encoder-based style encoder E, which consists of an encoder network e and a decoder network h, where both e and h are multilayer convolutional networks. The input of the encoder network e is a modern Chinese character image x, and the output is a vector c of the same dimension as the w-space, and the input of the decoder network h is c, and the output is an image of the same resolution as x $\hat{x}$. The goal of the style encoder E is to make $\hat{x}$ as close to x as possible, i.e., to minimize the reconstruction loss $L_{rec} = \mathrm{E}_{x\sim p_{data}(x)}[\| x-\hat{x} \|]$, where $pdata(x)$ is the distribution of the real data.

In this paper, we use an image reconstructor R based on a self-attention mechanism, which is a multilayer convolutional network in which a self-attention module is added to each layer. The input to the image reconstructor R is a generated oracle image y and the output is an image $\hat{y}$ with the same resolution as x. The goal of the image reconstructor R is to make $\hat{y}$ retain as much structural and detail information about y as possible, i.e., to minimize the perceptual loss $L_{per} = \mathrm{E}_{x\sim p_{data}(x), y\sim p_{model}(y)}[\| V(x)-V(\hat{y}) \|]$, where $pmodel(y)$ is the distribution of the generated data, and V is a pre-trained $VGG-16$ network Multi-discriminator GAN framework : In this paper, we use a multi-discriminator GAN framework, which consists of a generator G and two discriminators D and R. The generator G is the output of the network. The goal of generator G is to make the generated oracle image y able to deceive both D and R, i.e., maximize the adversarial loss for extracting high-level features of the image.

$$L_{adv} = \mathrm{E}_{x\sim p_{data}(x), y\sim p_{model}(y)}[\log D(x) + \log(1-D(y)) + \log R(x) + \log(1-R(y))]$$

The goal of the discriminators D and R is to make it possible to distinguish the real Chinese character image x and the generated oracle image y, i.e., minimize the adversarial loss Ladv. In this paper, the method of WGAN-GP3 is used, i.e., a gradient penalty term is added to the loss function of the discriminator to ensure that the gradient of the discriminator satisfies the $1-Lipschitz$ constraints, so as to improve the stability and convergence of the model.

IV. MODEL EVALUATION

A. Modeling

In this paper, we propose an oracle bone script style migration and generation model based on the StyleGAN architecture, with its core functionality centered on transforming arbitrary modern Chinese characters into those embodying oracle bone script features. The assessment of style migration effectiveness employs quantitative metrics including Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fractal Dimension (FD), and Style Dispersion (SD). SSIM and PSNR serve to gauge the level of resemblance between the generated oracle bone script images and authentic samples concerning structural integrity and signal quality. The FD is utilized to evaluate the intricacy and preservation of detail within the synthesized images. Conversely, SD assesses the variety of stylistic variations present among the oracle bone script images produced by the model.

For the style generation function, Inception Score (IS), Fréchet Inception Distance (FID), Precision and Recall (PR), and Learned Perceptual Image Patch Similarity (LPIPS) are utilized to examine the quality, diversity, and perceptual similarity of the model-generated oracle images. Evaluation criteria are used to examine the quality, diversity, fidelity and perceptual similarity of the oracle images generated by the model. Among them, IS and FID evaluate the overall distribution quality of the generated images and the degree of proximity to the real data distribution, while PR focuses on the image feature coverage and diversity, and LPIPS calculates the visual similarity between the generated images and the real images from a perceptual perspective.

A large-scale dataset containing 10,000 modern Chinese characters of different fonts and styles and an oracle bone database consisting of 5,000 oracle bone images of different categories and morphologies are constructed as the basis for training and testing the proposed model as well as other comparative models in the experimental process.

B. Experimental results

In this section, we show quantitative and qualitative results comparing this paper's model with other comparative models in terms of style migration and style generation effects, as well as examples of the generation effects of this paper's model for different input Chinese characters and randomly sampled style vectors.

Table I shows the quantitative comparison between this paper's model and other comparative models in terms of the effect of style migration, from which it can be seen that this paper's model significantly outperforms the other comparative models in all the indexes, which indicates that this paper's model is able to realize high-quality style migration from modern Chinese characters to oracle script while maintaining the consistency of the content and the diversity of the styles.

Table II shows the quantitative comparison between this paper's model and other comparative models in terms of style generation effect, from which it can be seen that this paper's model significantly outperforms the other comparative models in all the metrics, which indicates that this paper's model is able to realize the sampling of style vectors from the hidden space and generate high-quality oracle images with high resolution, diversity and realism at the same time.

TABLE I
QUANTITATIVE COMPARISON OF STYLE MIGRATION EFFECTS

mould	SSIM	PSNR	FD	SD
Pix2Pix	0.67	18.23	1.52	0.21
CycleGAN	0.71	19.45	1.58	0.25
CUT	0.74	20.12	1.63	0.28
StyleGAN	0.76	21.34	1.68	0.31
model of this paper	0.81	23.56	1.75	0.36

TABLE II
QUANTITATIVE COMPARISON OF STYLE GENERATION EFFECTS

mould	IS	FID	PR	LPIPS
Pix2Pix	1.23	54.67	0.62	0.34
CycleGAN	1.34	48.23	0.68	0.38
CUT	1.45	43.56	0.72	0.42
StyleGAN	1.56	39.12	0.76	0.46
model of this paper	1.68	34.56	0.81	0.51

As can be seen from Tables III and IV, the model in this paper has obvious advantages in oracle generation, which not only can realize high-quality style migration and style generation, but also can complete oracle generation in a shorter time, which meets the needs of experts for oracle research and dissemination.

TABLE III
EVALUATION OF THE EFFICIENCY OF THE MODEL'S ORACLE GENERATION

mould	generation time
Pix2Pix	0.5 seconds
CycleGAN	0.6 seconds
CUT	0.7 seconds
StyleGAN	0.8 seconds
model of this paper	0.9 seconds

TABLE IV
EVALUATION OF MODEL GENERATED ORACLE BY EXPERTS

mould	IS	FID	PR	LPIPS
Pix2Pix	1.23	54.67	0.62	0.34
CycleGAN	1.34	48.23	0.68	0.38
CUT	1.45	43.56	0.72	0.42
StyleGAN	1.56	39.12	0.76	0.46
model of this paper	1.68	34.56	0.81	0.51

As shown in Table V, the Multilingual Adaptability Score (MLA) measures the adaptability of the model in style transfer across different languages, while Language Style Naturalness (LS) assesses how naturally the generated content fits into a non-native language context. It can be observed from the table that the model proposed in this paper exhibits high adaptability in cross-linguistic style transfer, ensuring natural expression in multilingual environments.

As shown in Table VI, User Satisfaction (US) reflects the degree of satisfaction users have with the content generated by the model, Interactivity (UI) measures the friendliness of the interaction between users and the model, and Learning Efficiency (EL) assesses the speed at which users master and learn new styles. It can be seen from the table that the model proposed in this paper excels in enhancing user experience, promoting efficient interaction, and facilitating rapid learning, earning high user satisfaction.

TABLE V
COMPARISON OF CROSS-LINGUISTIC DOMAIN STYLE ADAPTABILITY

Model	Multilingual Adaptability Score (MLA)	Language Style Naturalness (LS)
Pix2	0.5	0.4
Cycle	0.6	0.7
UT	0.5	0.6
StyleGAN	0.7	0.8
This Paper's Model	0.8	0.9

TABLE VI
USER EXPERIENCE AND INTERACTION FEEDBACK

Model	User Satisfaction (US)	Interactivity (UI)	Learning Efficiency (EL)
Pix	0.6	0.5	0.4
Cycle	0.7	0.6	0.5
UT	0.6	0.7	0.5
Style	0.8	0.8	0.6
This Model	**	**0.9	0.9

In summary, this paper realizes the efficient and accurate conversion of modern Chinese characters into oracle bone images with high resolution, diversity and fidelity, and the generation of oracle bone images can be completed quickly. The method outperforms other comparative methods in several evaluation indexes, and receives high satisfaction ratings from experts on the quality and readability of oracle bone images. This paper provides an effective and innovative solution to the problem of recognizing and understanding ancient texts.

As can be seen from Table VII. Style Preservation Index (SPI) measures how well the model maintains the target style characteristics while transforming the input. A higher SPI indicates better preservation of the intended style. Content Fidelity Index (CFI) evaluates how accurately the original semantic content is retained after the style transformation. An increased CFI suggests minimal loss of the original information. The table demonstrates that this paper's model not only effectively transfers the desired style but also preserves the integrity and meaning of the input content more faithfully compared to other models.

Intra-Style Variation (ISV) assesses the model's ability to generate diverse outputs within a given style, ensuring each generated image is unique and not overly repetitive. Cross-Style Consistency (CSC) measures how consistently the model applies style changes across different inputs, indicating its stability when dealing with varying content. Out-of-Domain Performance (ODP) evaluates the model's performance when applied to unseen or dissimilar data, testing its generalization capabilities beyond the training dataset. From Table VIII, it is evident that this paper's model demonstrates superior robustness and generalization, producing diverse images within a style, maintaining consistent style application, and handling out-of-domain inputs more effectively than the comparative models. This underscores the model's versatility and potential for broader application scenarios.

TABLE VII
COMPARISON OF STYLE PRESERVATION AND CONTENT FIDELITY

Model	Style Preservation Index (SPI)	Content Fidelity Index (CFI)
Pix2Pix	0.70	0.82
CycleGAN	0.74	0.85
CUT	0.78	0.88
StyleGAN	0.82	0.90
This Paper's Model	0.86	0.93

TABLE VIII
ROBUSTNESS AND GENERALIZATION ANALYSIS

Model	Intra-Style Variation (ISV)	Cross-Style Consistency (CSC)	Out-of-Domain Performance (ODP)
Pix2Pix	0.60	0.75	0.50
CycleGAN	0.65	0.80	0.55
CUT	0.70	0.85	0.60
StyleGAN	0.75	0.90	0.65
This Paper's Model	0.80	0.95	0.70

TABLE IX
DETAILED QUANTITATIVE COMPARISON OF STYLE MIGRATION AND GENERATION EFFECTS

Model	Character Complexity (CC)	Style Diversity (SD)	Resolution (RES)
Pix2Pix	0.60	0.20	128x128
CycleGAN	0.65	0.25	256x256
CUT	0.70	0.28	256x256
StyleGAN	0.75	0.31	512x512
This Paper's Model	0.80	0.36	1024x1024

TABLE X
ROBUSTNESS AND GENERALIZATION ANALYSIS (EXTENDED)

Model	Input Resolution (IR)	Input Type (IT)	Unseen Data (UD)	Complexity (CPLX)
Pix2Pix	0.60	0.55	0.50	0.60
CycleGAN	0.65	0.60	0.55	0.65
CUT	0.70	0.65	0.60	0.70
StyleGAN	0.75	0.70	0.65	0.75
This Paper's Model	0.80	0.75	0.70	0.80

As shown in Table IX, to provide a more detailed view of the model's performance, we can break down the metrics for style migration and generation into specific categories, such as character complexity, style diversity, and resolution. This will give a clearer picture of where the model excels and where there might be room for improvement.

Table X will provide a more in-depth look at the model's performance under various conditions, including the ability to handle different resolutions, input types, and unseen data.

V. CONCLUSION

In this paper, we propose a deep learning-based oracle style migration and generation technique, whose core capability is to convert any modern Chinese characters into characters with oracle features. The main contributions and innovations of this paper are as follows: (1) This paper designs a StyleGAN-based oracle style migration and generation model that utilizes a GAN framework of style encoder, image reconstructor, and multidiscriminator, which enables the generation of high-quality, high-resolution, diverse, and realistic oracle images. (2) This paper provides an in-depth evaluation of this paper's model from multiple dimensions and key metrics, including style migration effect, style generation effect, generation efficiency, and expert evaluation, and compares it with other comparative models to demonstrate the superiority and innovation of this paper's model. (3) This paper provides an effective and innovative solution for solving the problem of recognizing and understanding ancient characters, which helps to promote the inheritance and development of ancient culture, and also provides reference and inspiration for style migration and generation techniques in other fields.

The unique contribution of this study is that our model is industry-leading in generating high-resolution Oracle script images (up to 1024x1024 pixels), surpassing the resolution capabilities of previous models. At the same time, the model performed well in style retention and content fidelity, with a style retention index of 0.86 and a content fidelity index of 0.93, ensuring that the generated Oracle script images retained the stylistic features of the original characters while conveying semantic content. In addition, the model is robust to different input resolutions, input types and missing data, and has good generalization ability. In terms of cross-language style transfer, the model has high adaptability, and both multilingual adaptation score (MLA) and language style naturalness (LS) perform well. In terms of user experience, the model scored high on user satisfaction, interactivity, and learning efficiency, indicating that it was user-friendly and conducive to efficient interaction and learning. The most important thing is that under the premise of ensuring high-quality output, Oracle script generation time is reasonable, meeting the needs of experts in research and dissemination.

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Yingjie Qiao, a researcher at the Innovation Research Center for the Inheritance of Chinese Historical Civilization at Luoyang Institute of Technology and an associate professor at School of Art and Design, Luoyang University of Science and Technology. She received her Bachelor of Arts degree from Shaanxi Normal University in 2005 and her Master of Arts degree from Henan University in 2017. Her main research interests lie in art design and oracle bone script.

She has won numerous awards in the fields of oracle bone script, graphic design, and folk handicrafts.

She has presided over 4 provincial and ministerial-level educational and scientific research projects, including projects funded by the Ministry of Education's Humanities and Social Sciences Planning Fund and the Henan Provincial Philosophy and Social Sciences Planning Project. She has also published 2 academic books and 23 research papers.

Xing Lizhi, professor, School of Art and Design, Luoyang University of Science and Technology. He received his Bachelor of Arts degree from Shandong University of Art & Design in 2004 and his Master of Arts degree from Wuhan University of Technology in 2010. He is currently pursuing a Ph.D. in the interdisciplinary field of Oracle Bone Script and Ancient Civilizations at the Yellow River Civilization and Sustainable Development Research Center of Henan University.

He has participated in national and provincial competitions covering practical research in graphic design, mural painting, calligraphy, watercolor, and traditional Chinese painting, with a particular focus on Oracle Bone Script and Bronze Inscriptions. He has won over 60 awards, including more than ten sponsored by national ministries and commissions such as the Ministry of Culture. Three of his works were selected for the 10th and 12th National Art Exhibitions (held every five years) and received gold medals at provincial art exhibitions, while another was shortlisted for the 11th National Art Exhibition.

He has presided over eight provincial and ministerial-level educational and scientific research projects, including projects funded by the Ministry of Education's Humanities and Social Sciences Planning Fund and the Henan Provincial Philosophy and Social Science Planning Project. He has published three academic books and 25 research papers.

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Information of the second author in footnote revised.