

# CreativeSynth: Creative Blending and Synthesis of Visual Arts based on Multimodal Diffusion

Nisha Huang<sup>1,2</sup> Weiming Dong<sup>1,2</sup> Yuxin Zhang<sup>1,2</sup> Fan Tang<sup>3</sup>

Ronghui Li<sup>4</sup> Chongyang Ma<sup>5</sup> Xiu Li<sup>6</sup> Changsheng Xu<sup>1,2</sup>

<sup>1</sup>School of Artificial Intelligence, UCAS <sup>2</sup>MAIS, Institute of Automation, CAS

<sup>3</sup> Institute of Computing Technology, CAS <sup>4</sup>Tsinghua University

<sup>5</sup>ByteDance Inc. <sup>6</sup>Shenzhen International Graduate School, Tsinghua University

<https://anonymous.4open.science/r/CreativeSynth-52A8>



Figure 1. Our CreativeSynth unified framework is capable of generating personalized digital art when supplied with an art image, drawing on prompts from either unimodal or multimodal prompts. This methodology not only yields artwork with high-fidelity realism but also effectively upholds the foundational concepts, composition, stylistic elements, and visual symbolism intrinsic to genuine artworks. CreativeSynth supports a wide array of intriguing applications, including (a) image variation, (b) image editing, (c) style transfer, (d) image fusion, and (e) multimodal blending.

## Abstract

Large-scale text-to-image generative models have made impressive strides, showcasing their ability to synthesize a vast array of high-quality images. However, adapting these models for artistic image editing presents two significant challenges. Firstly, users struggle to craft textual prompts that meticulously detail visual elements of the input image. Secondly, prevalent models, when effecting modifications in specific zones, frequently disrupt the overall artistic style,

complicating the attainment of cohesive and aesthetically unified artworks. To surmount these obstacles, we build the innovative unified framework CreativeSynth, which is based on a diffusion model with the ability to coordinate multimodal inputs and multitask in the field of artistic image generation. By integrating multimodal features with customized attention mechanisms, CreativeSynth facilitates the importation of real-world semantic content into the domain of art through inversion and real-time style transfer. This allows for the precise manipulation of image style and con-

tent while maintaining the integrity of the original model parameters. Rigorous qualitative and quantitative evaluations underscore that CreativeSynth excels in enhancing artistic images' fidelity and preserves their innate aesthetic essence. By bridging the gap between generative models and artistic finesse, CreativeSynth becomes a custom digital palette.

## 1. Introduction

If a picture is worth a thousand words, then two pictures can weave a narrative beyond measure. The boundaries of digital art continue to be pushed as artificial intelligence technologies [1–4] flourish in the field of art creation. These innovations, rooted in the synergy of natural language processing and generative paradigms, are redefining our approach to conceiving and creating digital masterpieces that resonate with the essence of human creativity and intent.

Diffusion models [5–7] have set the benchmark in terms of generation quality, skillfully transforming noise into recognizable high-resolution visual content. However, these approaches often encounter limitations in the granularity of control over subtle visual aspects and deep semantic elements, attributed to the disproportionate influence textual prompts exercise upon the resultant imagery. To break through this limitation and improve the ability to accurately edit artistic images, we introduce a more effective image prompt adapter [8] for enhancing the versatility of the model and the realism of the visual input, seamlessly transforming the image into a piece of vivid expressive space. This allows textual prompts to become flexible mediators of artistic transformation, responding with agility to changes induced by textual editing (see Fig. 1).

Precise control and editing of the content within any single image remain a significant challenge [1–4]. Current methods typically fail to capture subtle details [9–11] or require tedious manual adjustments for each input image [12, 13]. Furthermore, users often find it challenging to accurately describe the visual elements of a specific input image through text. Additionally, models tend to disrupt the overall artistic style when modifying certain specific areas, which complicates the maintenance of style unity and aesthetic integrity of the artwork. To address those problems, in this paper, we propose CreativeSynth, a revolutionary unified framework that integrates multimodal inputs with digital artworks. CreativeSynth not only focuses on generating images with realism but also retains fundamental artistic elements such as conceptual integrity, stylistic fidelity, and visual symbolism.

CreativeSynth introduces an innovative concept of customized art, transcending the limitations of traditional style transfer and text-guided image generation techniques, as

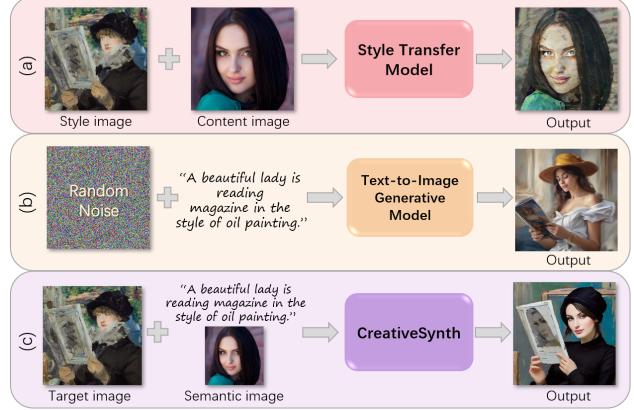


Figure 2. Comparative analysis of conceptual distinctions among (a) classical style transfer [14], (b) text-to-image synthesis [15], and (c) our CreativeSynth framework.

shown in Fig. 2. The two core mechanisms we propose, aesthetic maintenance and semantic fusion, enable CreativeSynth to perform a series of art image editing and generation tasks while preserving the individual visual characteristics of the artwork. During the image generation process, the aesthetic maintenance mechanism ensures the artist's original intent and the artwork's original style are not lost, as well as the overall aesthetic harmony when new visual elements are added. The semantic fusion mechanism emphasizes the synergy between multimodal inputs and visual art creation, enhancing the work's capacity for personalized customization and reflecting the user's intentions and narrative. Specific applications of CreativeSynth include image variation, image editing, style transfer, image fusion, and multimodal blending, as demonstrated in Fig. 1. To summarize, our contributions are:

- We introduce CreativeSynth, an innovative multimodal, multitasking unified art framework that enables the ability to edit arbitrary art images on a single platform.
- We employ advanced mechanisms for aesthetic maintenance, semantic fusion, and inversion coding. These techniques enable the maintenance of the intrinsic expression of the art image while integrating multimodal semantic information. The coherence of the artwork is greatly improved from both macro and micro aspects, ultimately realizing truly personalized creation.
- The experimental results prove that CreativeSynth demonstrates superior performance compared to other state-of-the-art methods in the current field of art image blending and synthesis.

## 2. Related Work

**Image style transfer.** Style transfer has been extensively studied as a common mechanism for generating artistic images guided by examples. Traditional style transfer research has evolved from patch matching methods [16] to deep convolutional neural networks learning approaches [17, 18]. AdaIN [14] employs conditional instance normalization for style transfer by aligning content and style feature statistics. ArtFlow [19] technique uses reversible neural flows to prevent content leakage. CAST, developed by [20], enhances arbitrary style transfer via contrastive learning, while the visual transformer-based StyTr<sup>2</sup> addresses image dependencies to maintain content integrity [21]. Recent diffusion-based text-driven methods including InST [12], StyleDrop [22], and DiffStyler [23] have broadened the domain with stylistically expressive and parameter-efficient approaches. While existing image style transfer methods primarily focus on learning and transferring artistic elements into a given content image (see Fig. 2(a)), our approach aims to create the appearance of specific content within a target painting.

**Text-to-image generation.** With the ability of neural networks to understand intricate natural language and visual representations, the field of image synthesis has made significant progress from textual descriptions [24]. Transformer-based architectures such as DALL-E [25] and its follow-up studies [6, 7] incorporate powerful attentional mechanisms to efficiently transform textual prompts into high-fidelity images. Similarly, VQ-VAE-2 [26] and its autoregressive model demonstrate the strong potential of combining textual and visual patterns through discrete latent spaces. These methods have achieved remarkable results, but they often do not allow for fine control of structural details [10, 27]. Diffusion models similar to Stable Diffusion [5] also exemplify the ability to generate high-quality images based on descriptions. Nonetheless, as shown in Fig. 2(b), these methods still face the challenge of generating images with styles that are inconsistent with textual prompts. Our research closely follows the previous work [1, 4, 27, 28], focusing on converting multimodal prompts into realistic artistic images and achieving innovations in reconstructing and editing existing images.

**Personalized image generation.** In order to incorporate specific styles or personalities into image generation, personalization, and style alignment has become an important area of research. For example, StyleGAN [29] has made impressive progress in personalized face generation. ControlNet [30] leverages “zero-convolution” fine-tuning on pre-trained diffusion models to enable diverse, prompt-driven image generation with spatial conditioning. In terms of

image restoration with constraints, ProSpect [13] attempts to preserve the style features of the reference image while adapting its content to fit the new context. In terms of achieving multi-image style consistency, Style Aligned [27] shows how multiple images can be stylistically consistent through a shared attention layer. Textual Inversion [4] introduces a method for embedding new “words” into the model space using as few as 3-5 images, allowing for nuanced linguistic guidance customization and demonstrating superior concept depiction capabilities across a range of tasks. [31] enables intuitive text-guided image edits by inverting images into the domain of a pre-trained model using meaningful text prompts. As demonstrated in Fig. 2(c), our work extends the above idea by enhancing the interaction between textual and artistic visual features made achievable through multimodal fusion.

## 3. Method

### 3.1. Overview

CreativeSynth incorporates information from text and image modalities to sample artwork based on guiding conditions. As illustrated in Fig. 3, this approach begins with encodings of semantic cues from images and textual prompts to lay the groundwork for condition guidance. Our framework then focuses on aesthetic maintenance by a dedicated processor that adjusts the semantic image style to be consistent with the artistic image through adaptive instance normalization. In the semantic fusion section, CreativeSynth employs a decoupled cross-attention mechanism that meticulously coordinates the interplay between visual and textual features, resulting in a cohesive synthesis rather than a sum of its parts. Finally, the sampling process is based on the principle of image inversion, which utilizes denoising techniques to reverse sample the image from the initial noise. Ultimately, CreativeSynth generates customized artworks that resonate with the given semantic prompts and chosen aesthetic style.

### 3.2. Condition Guidance

**Condition encoding.** The encoding process integrates text and image features using a decoupled cross-attention mechanism within the framework of a pre-trained Stable Diffusion model [5]. For a given text prompt  $P$ , the tokenizer and the text encoder from the pre-trained diffusion model are used to generate the text embeddings  $\mathbf{E}_{\text{text}} \in \mathbb{R}^{n \times d_{\text{text}}}$ :

$$\mathbf{E}_{\text{text}} = \mathcal{E}(\text{Tokenizer}(P)), \quad (1)$$

where  $n$  is the sequence length and  $d_{\text{text}}$  is the text embedding dimension.

Image encoding requires converting images into a suitable latent representation that can be processed by the generative model. For an input image  $\mathbf{I}$ , the encoding is com-

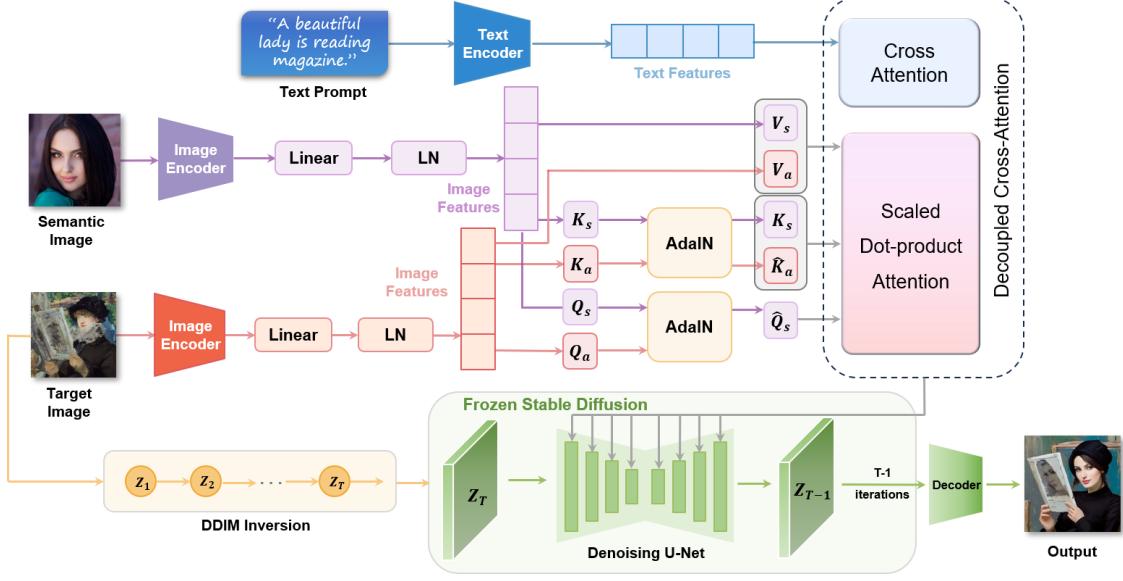


Figure 3. The overall structure of CreativeSynth. Text features and image features are first acquired from separate text and image encoders, respectively. Then, target and semantic images are interacted with by applying AdaIN to focus on image art features. An innovative decoupled cross-attention mechanism is employed to fuse the attention between the multimodal inputs, which is subsequently integrated into a U-Net architecture. The target image is transformed into a latent variable  $z_T$  via DDIM Inversion, and the final output is refined through a denoising network.

puted by a forward pass through the VAE’s encoder network of the Stable Diffusion model:

$$\mathbf{z}_I = \mathcal{E}_{\text{VAE}}(\mathbf{I}). \quad (2)$$

Unlike the existing U-Net cross-attention architecture, which uses two paths to process text and image features separately, each path consists of specialized cross-attention layers that are dedicated to either text features or image features without interfering with each other.

### 3.3. Aesthetic Maintenance

**Style alignment.** We introduce a style alignment processor to adjust the model’s attention mechanism and normalization layers. It achieves an adaptive style blending between the aesthetic image and the semantic image. Specifically, we utilize the adaptive instance normalization (AdaIN) [14] technique. It adjusts the semantic image  $I_s$  to have the same mean and variance as the features of the aesthetic image  $I_a$ . The AdaIN formula is as follows:

$$\hat{\mathbf{Q}}_s = \text{AdaIN}(\mathbf{Q}_s, \mathbf{Q}_a), \quad (3)$$

$$\hat{\mathbf{K}}_s = \text{AdaIN}(\mathbf{K}_s, \mathbf{K}_a), \quad (4)$$

where  $\mathbf{Q}_s$  and  $\mathbf{K}_s$  are the query and key of the semantic image, and  $\mathbf{Q}_a$  and  $\mathbf{K}_a$  are the query and key of the aesthetic image, respectively. The AdaIN operation is defined as:

$$\text{AdaIN}(x, y) = \sigma(y) \left( \frac{x - \mu(x)}{\sigma(x)} \right) + \mu(y), \quad (5)$$

where  $\mu(x)$  is the mean of the semantic features,  $\sigma(x)$  is the standard deviation of the semantic features, and  $\mu(y)$  is the mean of the style features.

**Shared attention.** Shared attention combines the characteristics of artistic images and semantic images, updating the information in the semantic images based on the style of the artistic image.  $\hat{\mathbf{Q}}_s$  and  $\mathbf{K}_{as}$  represent the normalized query and shared key, respectively, while  $\mathbf{V}_{as}$  denotes the value:

$$\mathbf{K}_{as} = \begin{bmatrix} \mathbf{K}_a \\ \hat{\mathbf{K}}_s \end{bmatrix}, \quad \mathbf{V}_{as} = \begin{bmatrix} \mathbf{V}_a \\ \mathbf{V}_s \end{bmatrix}. \quad (6)$$

The keys and values are aggregated together from the target image and the reference image, while the query only represents the attributes of the target image. The application of the scaled dot-product attention mechanism is as follows:

$$\mathbf{Z}' = \text{Attention}(\hat{\mathbf{Q}}_s, \mathbf{K}_{as}^T, \mathbf{V}_{as}) = \text{Softmax} \left( \frac{\hat{\mathbf{Q}}_s \mathbf{K}_{as}^T}{\sqrt{d}} \right) \mathbf{V}_{as}, \quad (7)$$

where  $d$  is the dimensionality of the keys and queries.

### 3.4. Semantic fusion

**Decoupled cross attention.** Text features are regarded as the context for attention, and the editing text undergoes a cross-attention mechanism without sharing attention with the aesthetic image features. By decoupling the cross-attention mechanism, the shared attention results of images

and the cross-attention results of texts are combined for the final image generation. Each information stream (image and text features) is processed through its own cross-attention layer, after which they are merged to produce the final modified image feature  $\mathbf{Z}''$ :

$$\mathbf{Z}'' = \mathbf{Z}' + \text{Softmax} \left( \frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}} \right) \mathbf{V}, \quad (8)$$

here  $\mathbf{Q}$ ,  $\mathbf{K}$ ,  $\mathbf{V}$  are the transformed query, key, and value matrices of the text features. The contribution of each decoupled attention operation is summed up to influence the final feature representation.

### 3.5. Sample Process

**Image inversion.** In order to reconstruct a real image under a given conditional text, we need to perform a reverse process to recover the image from random noise. We employ the deterministic Denoising Diffusion Implicit Models (DDIM) as our core denoising technique. Specifically, we use the following reverse formula of DDIM to restore the original image:

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( x_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right) + \sigma_t z, \quad (9)$$

where  $\alpha_t$  is the step size factor in the denoising process,  $\epsilon_\theta$  is the predicted noise,  $z$  is an optional noise vector used to increase randomness, and  $\sigma_t$  is a factor that regulates the noise intensity.

In the sampling process, we design an inversion callback function, which aims to adjust the latent space vectors at the end of each inversion step to ensure the text alignment of the image. For this, we define the following callback function:

$$\text{Callback}(z_t, t) = \begin{cases} z_T, & \text{if } t = T, \\ z_t, & \text{otherwise.} \end{cases} \quad (10)$$

Here  $z_t$  denotes the latent variable corresponding to the temporal index  $t$ , which is substituted with a pre-computed vector derived via a technique DDIM inversion [31]). This ensures that throughout the diffusion process, our optimized latent space vector remains highly consistent with the inherent attributes of the target image.

**Aesthetic maintenance image generation.** Using pre-processed latent vectors, our model generates a series of images that follow user-provided text input while maintaining style alignment provided by a reference image. To achieve this, we introduce the IP-Adapter [8], which leverages embeddings from the reference image to guide the generation process. Given a target prompt ( $P$ ) and a negative prompt ( $NP$ ), the IP-Adapter (IPA) calculates the embeddings of the prompts based on the following formula:

$$(E_P, E_{NP}) = \text{IPA}(P, NP, I_a), \quad (11)$$

where  $I_a$  symbolizes the artistic image.

## 4. Experiments

### 4.1. Implementation Details

The Stable Diffusion XL (SDXL) [15] model employed in our experiments has undergone pre-training on an extensive corpus of text-image pairs. This pre-training regimen enables the exploitation of the model’s full potential in terms of representational capacity. To ensure experimental consistency, we have standardized the number of generation steps and the guidance scale at 30 and 5.0, respectively. Furthermore, the input images utilized in the experiments are uniformly scaled to a resolution of  $1024 \times 1024$  pixels for both the image reversal process and subsequent image synthesis tasks. On a single NVIDIA L40 GPU, each image takes five seconds to generate.

### 4.2. Qualitative Evaluation

**Image fusion** In this analysis, we conduct baseline comparisons for image fusion tasks involving models such as Image Mixer [32], Kosmos-G [33], and VD [11]. Qualitative results can be seen in Fig. 4. Image Mixer and Kosmos-G tend to generate results with subdued stylistic expression, often producing images that are more realistic than artistic. Meanwhile, VD demonstrates a uniform high saturation in artistic expressiveness across various outputs but fails to capture the nuances of distinct styles. In contrast, our method consistently excels in style rendering, effectively incorporates semantic information, and yields harmonious fusion results that exhibit both aesthetic appeal and artistic quality.

**Text guided image editing** To accurately assess model performance, we conduct baseline comparisons for the task of single-image text editing. As shown in Fig. 5, our model takes succinct personalized text descriptions as input and successfully performs operations such as semantic introduction, facial attribute modification, and complex scene recreation across a range of different scenes and objects. For a comprehensive evaluation of our method, we select several advanced baseline models for comparison, including IP-Adapter [8], ProSpect [13], DreamBooth [1], Textual Inversion [4], SDXL I2I [15], Instruct Pix2Pix [9], Masactrl [10], and Versatile Diffusion (VD) [11].

Based on the results, although the IP-Adapter generates results of superior quality, it fails to preserve the non-editing information of the target image. In terms of style consistency, some models like ProSpect, DreamBooth, and SDXL I2I exhibit high congruence with the target image. However, Instruct Pix2Pix and Masactrl often damage the composition and content of the target image during editing, introducing distortions and unnatural artifacts. For instance,

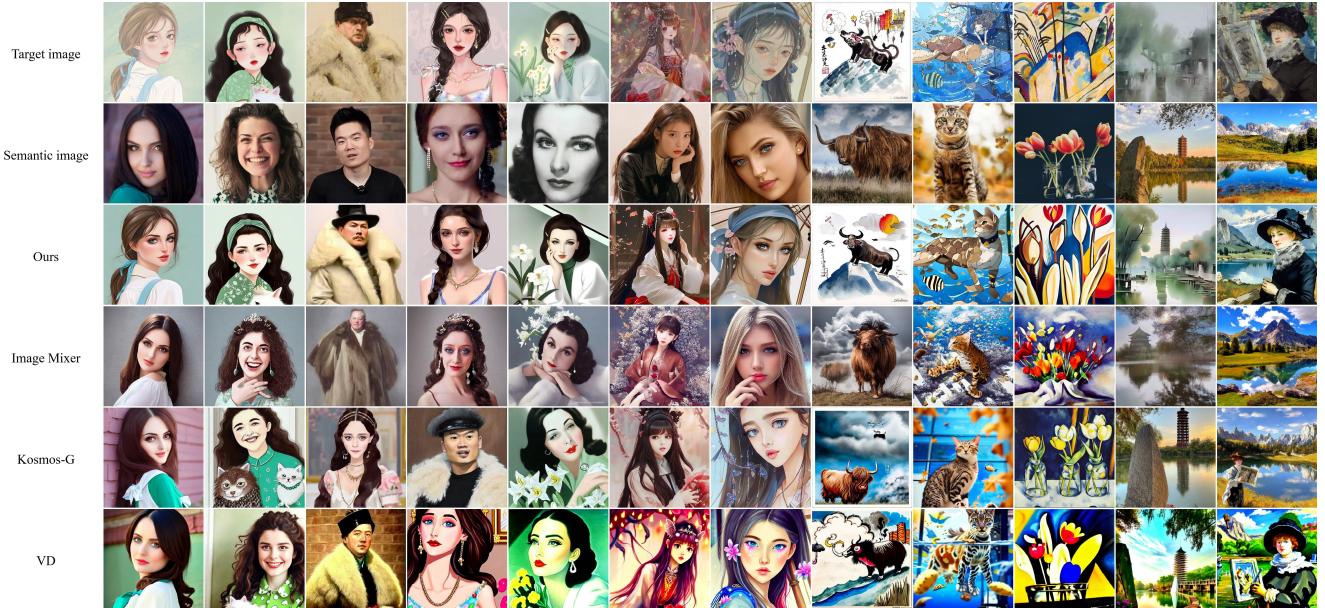


Figure 4. Qualitative comparisons of our proposed CreativeSynth with other extant methods. The results offer a visualization of image fusion between artistic and real images.

Table 1. Statistics of quantitative comparison with state-of-the-art methods. Specific metrics include aesthetic scores, CLIP-T, CLIP-I and human rates. The best results are in **bold** while the second best results are marked with underline.

	Ours	IP-Adapter	ProSpect	DreamBooth	TI	SDXL I2I	Instruct P2P	Masactrl	VD	Image Mixer	Kosmos-G
Aesthetic Score $\uparrow$	<b>7.563</b>	<u>7.249</u>	6.297	6.216	6.441	6.636	5.344	5.707	6.818	7.151	6.125
CLIP-T $\uparrow$	<b>59.123</b>	57.956	<u>58.004</u>	46.792	48.576	57.981	55.203	45.147	53.516	-	-
CLIP-I $\uparrow$	<b>52.067</b>	-	-	-	-	-	-	-	44.973	48.349	<b>50.564</b>
Overall Preference	-	24.1%	19.2%	1.5%	3.0%	12.9%	3.3%	14.7%	8.6%	20.3%	26.1%
Aesthetic Preference	-	34.2%	13.4%	44.1%	4.6%	18.7%	10.1%	24.1%	8.6%	28.4%	31.6%
Semantic Preference	-	17.7%	10.6%	4.1%	5.1%	18.0%	6.1%	9.4%	12.9%	21.5%	32.4%

images processed by Instruct Pix2Pix show obvious ghosting effects on headphones and ice cream, while Masactrl faces challenges in generating specific and realistic human faces. ProSpect and SDXL I2I perform admirably in preserving the semantic content of the original image, but often experience significant alterations in key features such as facial details of people, impacting the image’s authenticity and credibility. In contrast, DreamBooth’s results display very limited input image information changes, leading to the production of images that nearly do not align with the text editing requirements, thus limiting their potential for practical application. Lastly, Textual Inversion and VD can generate quite distinctive artworks, which are creative but still deviate significantly from the target image in terms of style and semantic preservation.

Compared to baselines, our results guarantee a high level of content fidelity and stylistic coherence during image modification. The altered images retain the principal structure of the original while integrating new attributes or alterations in accordance with text-based directives. In the

domain of facial attribute editing, our method yields facial features that are both more natural and realistic, minimizing visual anomalies and undue artistic alterations. Furthermore, our approach facilitates the effective reconstruction and editing of intricate scenes without disrupting the global composition of the image.

### 4.3. Quantitative Evaluation

To extensively evaluate the performance of our proposed method, this paper uses three key metrics—aesthetic score [34], CLIP-T [35], and CLIP-I [35]—for quantitative comparison with the current state-of-the-art methods. The aesthetic score reflects the visual appeal and artistic quality of the generated images, CLIP-T characterizes the semantic consistency between the generated images and the edited text, while CLIP-I indicates the visual and content coherence between the generated images and the target images. The comparison results are shown in Table 1. In terms of aesthetic score, our method significantly surpasses other methods, achieving the highest average score of 7.563,

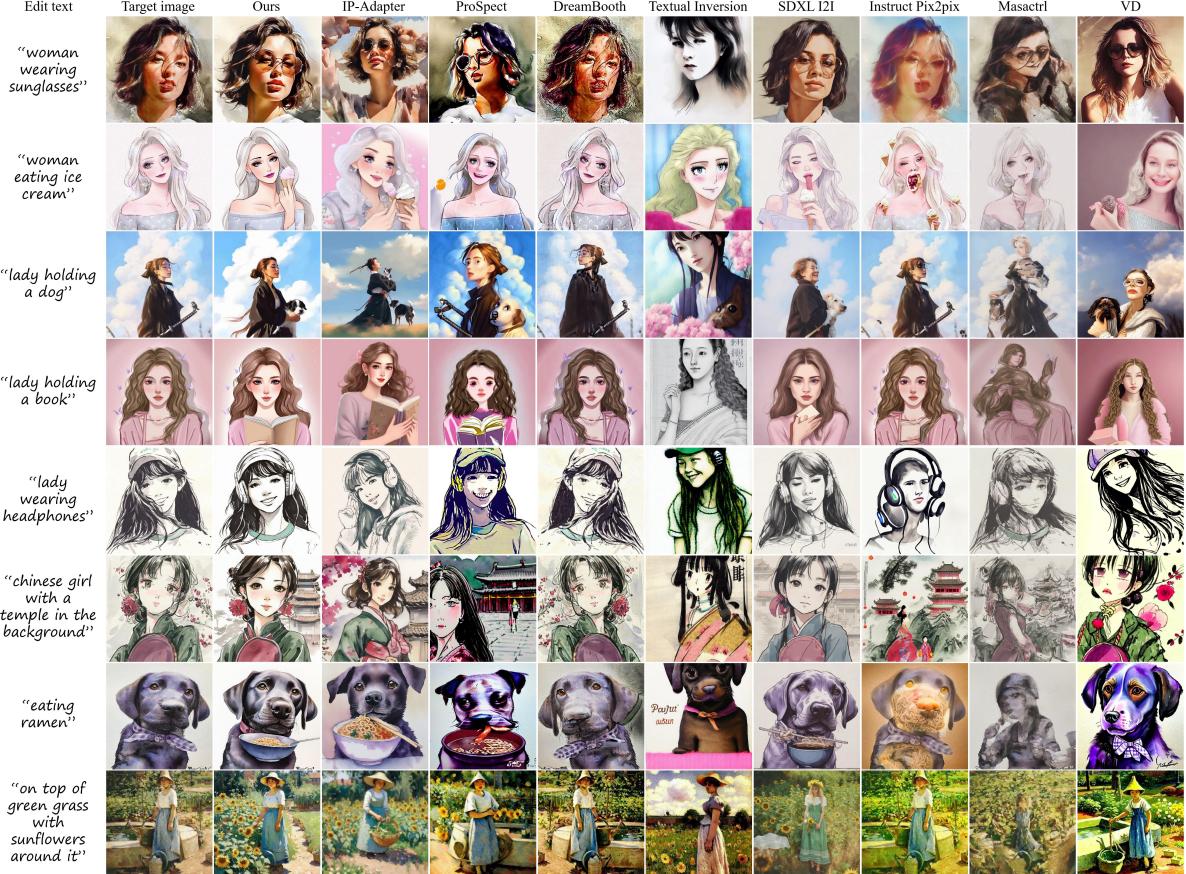


Figure 5. Visual comparison of our proposed CreativeSynth with state-of-the-art methods for text-guided editing of diverse types of art images.

demonstrating its outstanding performance in overall aesthetic appeal. The CLIP-T score quantifies the consistency of the generated images with the given text description. The higher the score, the more accurately the image reflects the content of the text description. Our method tops this assessment with a score of 59.123, indicating its efficient capability to reproduce the semantic information specified by the text in images. Our work also exhibit superior performance on the CLIP-I metric, highlighting our method’s capability in maintaining visual semantic. The score indicates that our method is able to preserve consistent visual quality and detail fidelity when considering image fusion. In summary, our method offers a balanced high-quality image generation solution as a whole, enabling it to meet the diverse requirements of different usage scenarios.

**User study** We benchmark CreativeSynth with ten other leading-edge image-generation techniques to determine which generates the most favored artistic outcomes. We presented each participant with 50 randomly selected sets of results, displaying the images produced by CreativeSynth

and an alternative method in no particular order. We asked participants to identify the results that (1) were the most visually pleasing overall, (2) most closely matched the artistic expression of the target image, and (3) most closely related to the editorial semantics of the text or image. In the end, we obtained 11,850 votes from 79 participants, and the percentage of votes for each method is detailed in rows 4 – 6 of Table 1. It is worth noting that CreativeSynth is particularly popular in the categories of ink drawing, oil painting, and digital art.

#### 4.4. Ablation Study

**Mechanism dissection** To deeply investigate the underlying mechanisms of our proposed method, we conduct a series of ablation experiments. We remove AdaIN, inversion, and IPA, respectively, to observe their impact on the generated image variations. As Fig. 6(a) demonstrates, the absence of AdaIN leads to discrepancies in the colors of the results compared to the style image. Without inversion, there is a significant difference in the facial feature details of the generated image relative to the input semantic image.

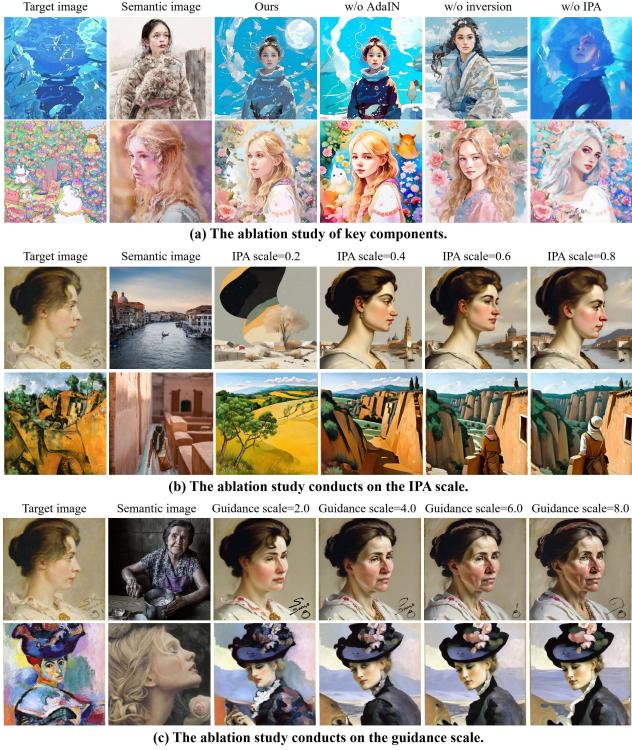


Figure 6. Results of ablation study on (a) AdaIN, inversion, and IPA, (b) IPA scale, and (c) guidance scale.

In the absence of IPA, consistent character information is not accurately introduced. However, the complete model retains style information and better incorporates semantic information.

**IPA** As Fig. 6(b) shows, we fine-tune the scale of IPA and record the changes in the generated images across various scales. With an increase in the IPA scale, the generated images more accurately reflect the expected style and content under the given conditions, demonstrating IPA’s crucial role in controlling the generation process. Furthermore, we note that a proper increase in IPA scale significantly enhances the flexibility of image editing, allowing for more refined style adjustments and content updates.

**Condition guidance** By analyzing the visual results provided in Fig. 6(c), we discover that as the guidance scale increases, the details of the results become richer and more precise, aligning closer to the target style. This set of experiments, supported by both the visual demonstration in Fig. 6(c), confirms that increasing the guidance scale significantly improves the clarity and detail representation of the images, as well as the controllability over the generated images, thereby enhancing their accuracy and editability. Consequently, adjusting the guidance scale parameter

effectively optimizes the performance of our image generation algorithm.

## 5. Conclusions and Future Work

In this paper, we present CreativeSynth, a unifying framework designed to enable creative fusion and synthesis of visual artworks. The primary aim is to infuse multimodal semantic information into the world of artworks. This process ensures the preservation of the inherent themes, emotions, and narratives of the art pieces, transcending a mere overlay of style onto natural images. In this way, each synthesized work is not only a visual fusion, but also an intersection of meaning and story; with a strong personality, a unique visual narrative, and an exclusive emotional depth. Experimental results have shown that CreativeSynth is not only popular for its visual results, but also highly effective in executing user-specific artistic editorial intent. In the future, we plan to apply this approach to different image generation architectures and to broaden its application to encompass other forms of media, such as video. With subsequent refinements and applications, our approach will help creators realize creative expression like never before.

## References

- [1] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. DreamBooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 22500–22510, 2023. [2](#), [3](#), [5](#)
- [2] Yoad Tewel, Rinon Gal, Gal Chechik, and Yuval Atzmon. Key-locked rank one editing for text-to-image personalization. In *ACM SIGGRAPH 2023 Conference Proceedings, SIGGRAPH ’23, New York, NY, USA*, 2023. Association for Computing Machinery. [2](#)
- [3] Rinon Gal, Moab Arar, Yuval Atzmon, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. Encoder-based domain tuning for fast personalization of text-to-image models. *ACM Transactions on Graphics (TOG)*, 42(4):1–13, 2023. [2](#)
- [4] Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion. In *International Conference on Learning Representations (ICLR)*, 2023. [2](#), [3](#), [5](#)
- [5] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10684–10695, 2022. [2](#), [3](#)
- [6] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022. [2](#), [3](#)

- [7] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. GLIDE: Towards photorealistic image generation and editing with text-guided diffusion models. In *International Conference on Machine Learning (ICML)*, 2022. 2, 3
- [8] Hu Ye, Jun Zhang, Sibo Liu, Xiao Han, and Wei Yang. Ip-adapter: Text compatible image prompt adapter for text-to-image diffusion models. 2023. 2, 5
- [9] Tim Brooks, Aleksander Holynski, and Alexei A Efros. Instructpix2pix: Learning to follow image editing instructions. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 18392–18402, 2023. 2, 5
- [10] Mingdeng Cao, Xintao Wang, Zhongang Qi, Ying Shan, Xiaohu Qie, and Yinqiang Zheng. Masactrl: Tuning-free mutual self-attention control for consistent image synthesis and editing. *arXiv preprint arXiv:2304.08465*, 2023. 2, 3, 5
- [11] Xingqian Xu, Zhangyang Wang, Gong Zhang, Kai Wang, and Humphrey Shi. Versatile diffusion: Text, images and variations all in one diffusion model. In *IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 7754–7765, 2023. 2, 5
- [12] Yuxin Zhang, Nisha Huang, Fan Tang, Haibin Huang, Chongyang Ma, Weiming Dong, and Changsheng Xu. Inversion-based style transfer with diffusion models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10146–10156, 2023. 2, 3
- [13] Yuxin Zhang, Weiming Dong, Fan Tang, Nisha Huang, Haibin Huang, Chongyang Ma, Tong-Yee Lee, Oliver Deussen, and Changsheng Xu. Prospect: Prompt spectrum for attribute-aware personalization of diffusion models. *ACM Transactions on Graphics (TOG)*, 42(6):244:1–244:14, 2023. 2, 3, 5
- [14] Xun Huang and Serge Belongie. Arbitrary style transfer in real-time with adaptive instance normalization. In *IEEE International Conference on Computer Vision (ICCV)*, pages 1501–1510, 2017. 2, 3, 4
- [15] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis. *arXiv preprint arXiv:2307.01952*, 2023. 2, 5
- [16] Bin Wang, Wenping Wang, Huaiping Yang, and Jiaguang Sun. Efficient example-based painting and synthesis of 2D directional texture. *IEEE Transactions on Visualization and Computer Graphics (TVCG)*, 10(3):266–277, 2004. 3
- [17] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Image style transfer using convolutional neural networks. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2414–2423, 2016. 3
- [18] Leon A. Gatys, Alexander S. Ecker, Matthias Bethge, Aaron Hertzmann, and Eli Shechtman. Controlling perceptual factors in neural style transfer. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3730–3738, 2017. 3
- [19] Jie An, Siyu Huang, Yibing Song, Dejing Dou, Wei Liu, and Jiebo Luo. ArtFlow: Unbiased image style transfer via reversible neural flows. In *IEEE/CVF Conferences on Computer Vision and Pattern Recognition (CVPR)*, pages 862–871, 2021. 3
- [20] Yuxin Zhang, Fan Tang, Weiming Dong, Haibin Huang, Chongyang Ma, Tong-Yee Lee, and Changsheng Xu. Domain enhanced arbitrary image style transfer via contrastive learning. In *ACM SIGGRAPH 2022 Conference Proceedings*, 2022. 3
- [21] Yingying Deng, Fan Tang, Weiming Dong, Chongyang Ma, Xingjia Pan, Lei Wang, and Changsheng Xu. Stytr<sup>2</sup>: Image style transfer with transformers. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 11326–11336, 2022. 3
- [22] Kihyuk Sohn, Lu Jiang, Jarred Barber, Kimin Lee, Nataniel Ruiz, Dilip Krishnan, Huiwen Chang, Yuanzhen Li, Irfan Essa, Michael Rubinstein, et al. Styledrop: Text-to-image synthesis of any style. In *Advances in Neural Information Processing Systems (NIPS)*, 2023. 3
- [23] Nisha Huang, Yuxin Zhang, Fan Tang, Chongyang Ma, Haibin Huang, Weiming Dong, and Changsheng Xu. Diff-styler: Controllable dual diffusion for text-driven image stylization. *IEEE Transactions on Neural Networks and Learning Systems*, pages 1–14, 2024. 3
- [24] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018. 3
- [25] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International Conference on Machine Learning (ICML)*, pages 8821–8831. PMLR, 2021. 3
- [26] Ali Razavi, Aaron Van den Oord, and Oriol Vinyals. Generating diverse high-fidelity images with vq-vae-2. *Advances in Neural Information Processing Systems (NIPS)*, 32, 2019. 3
- [27] Amir Hertz, Andrey Voynov, Shlomi Fruchter, and Daniel Cohen-Or. Style aligned image generation via shared attention. *arXiv preprint arXiv:2312.02133*, 2023. 3
- [28] Nisha Huang, Fan Tang, Weiming Dong, and Changsheng Xu. Draw your art dream: Diverse digital art synthesis with multimodal guided diffusion. In *ACM International Conference on Multimedia*, page 1085–1094, 2022. 3
- [29] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4401–4410, 2019. 3
- [30] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In *IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 3836–3847, 2023. 3

- [31] Ron Mokady, Amir Hertz, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Null-text inversion for editing real images using guided diffusion models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6038–6047, 2023. [3](#), [5](#)
- [32] Pinkney, Justin, 2024. Last accessed on 2024-01-10. [5](#)
- [33] Xichen Pan, Li Dong, Shaohan Huang, Zhiliang Peng, Wenhui Chen, and Furu Wei. Kosmos-g: Generating images in context with multimodal large language models. *arXiv preprint arXiv:2310.02992*, 2023. [5](#)
- [34] Beaumont, Romain and Schuhmann, Christoph, 2024. Last accessed on 2024-01-15. [6](#)
- [35] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning (ICML)*, pages 8748–8763, 2021. [6](#)
- [36] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. *arXiv preprint arXiv:2010.02502*, 2020. [10](#)

## Appendix

### A. Diffusion

The diffusion process is simulated through a gradual noise addition process, where noise is progressively introduced to the clear original image  $x_0$ , generating a series of transitional latent variables  $(x_1, \dots, x_T)$ . In the denoising diffusion model, this process is defined as:

$$x_t = \sqrt{\bar{\alpha}_t}x_0 + \sqrt{1 - \bar{\alpha}_t}\epsilon_\theta(x_{t-1}, t),$$

where  $\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$  is the cumulative product factor for time step  $t$ , and  $\epsilon$  is a neural network model learned from random noise. In this process, we gradually apply forward noising to the original image  $x_0$ , creating a series of increasingly noised images  $x_1, x_2, \dots, x_T$  until an image that is nearly pure noise  $x_T$  is generated. Subsequently, we reconstruct the image using a reverse process, that is, by denoising steps learned step by step, we trace back from the noisy image  $x_T$  to the original image  $x_0$ . The key to our approach is the Denoising Diffusion Implicit Models (DDIMs) [36], which enables precise control over synthesis, serving as the backbone of the algorithm. DDIM employs a non-Markovian diffusion process, characterized by a sequence of forward noising steps followed by a reverse denoising procedure.

In our method, the reverse diffusion process follows the formal representation below to progressively restore the la-

tent clean image:

$$\begin{aligned} \mathbf{z}_{t-1} = & \sqrt{\alpha_{t-1}} \left( \frac{\mathbf{z}_t - \sqrt{1 - \alpha_t}\epsilon_\theta(\mathbf{z}_t, t)}{\sqrt{\alpha_t}} \right) \\ & + \sqrt{1 - \alpha_{t-1}}\epsilon_\theta(\mathbf{z}_t, t), \end{aligned}$$

where  $\alpha_t$  represents the steps of the predetermined variance schedule, and  $\epsilon_\theta$  is a parameterized neural network responsible for predicting the noise component in the image at time  $t$ . This process starts from the initial latent representation  $\mathbf{z}_T$  obtained from a prior noise distribution  $\mathcal{N}(0, \mathbf{I})$  and gradually decreases the noise until the original image representation in the latent space  $\mathbf{z}_0$  is completely restored. In this way, our model can perform precise image synthesis while providing good control and predictability over the synthesis process.

### B. Additional User Study

To further understand the necessity of our proposed idea, we also designed the following questions in the user research questionnaire: (1) whether the idea is necessary, (2) whether it creates realistic artworks, and (3) whether the result is novel and interesting. Finally, we collected 237 votes from 79 participants. The voting results showed that a percentage of 94.9% supported the necessity of our idea, the potential of the idea to be applied in practice, and the possibility to fulfill a specific need. In addition, 91.1% of the participants believed that it is indeed possible to create highly realistic works of art based on our idea, which shows the credibility of our technical realization and the recognition of the expected results. Most strikingly, a whopping 96.2% found the artworks generated by our idea to be innovative and appealing. In view of this, our idea is not only widely recognized by the potential user community, but also has some prospects for practical application.

### C. More results

The additional results of CreativeSynth are presented in Figs. 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19. These results demonstrate the performance of our model in terms of diversity and quality.

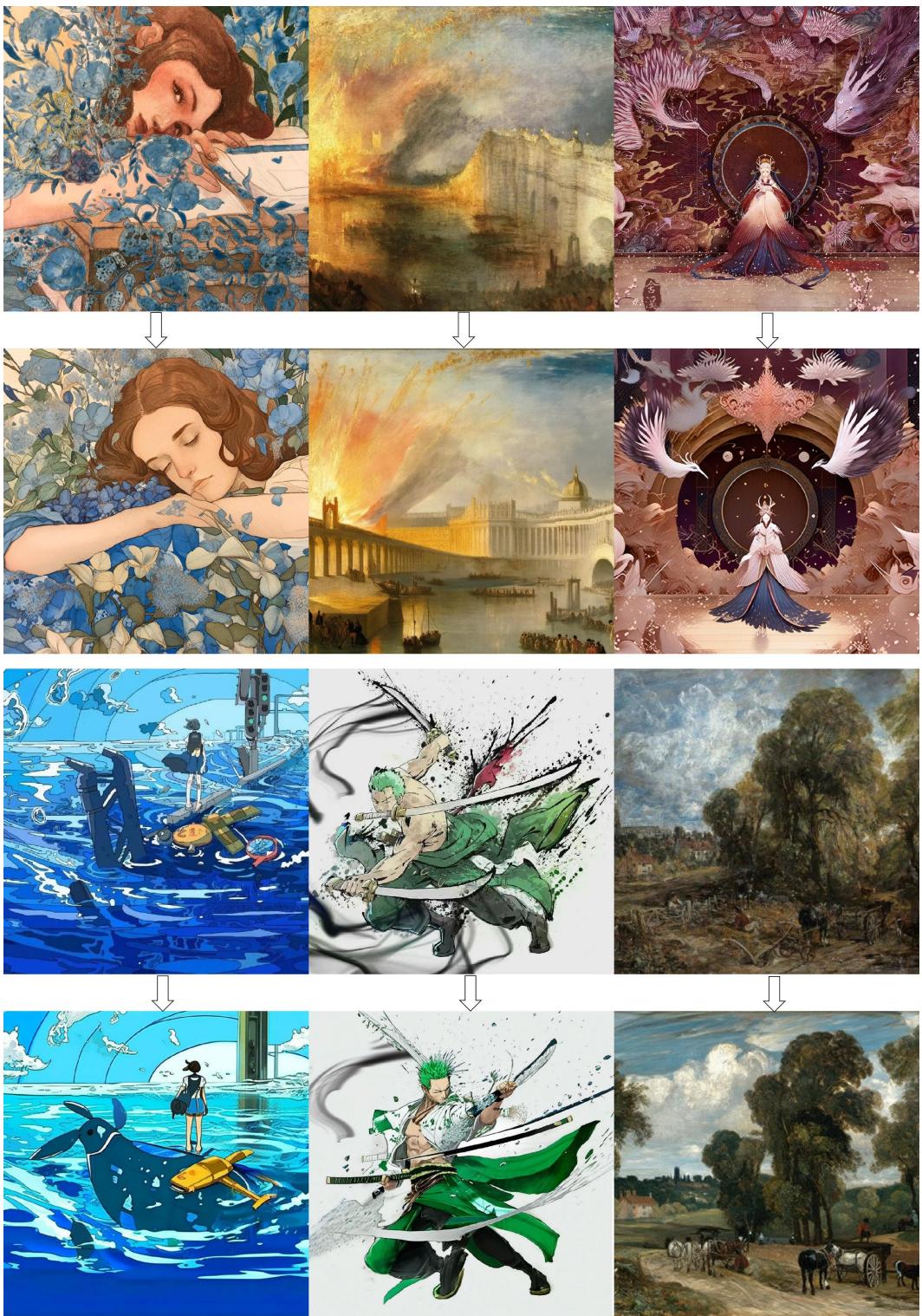


Figure 7. More results by CreativeSynth.



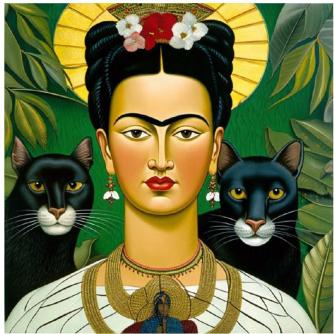
"Beautiful lady holding a dog."



"Woman eating ice cream."



"Beautiful lady holding a dog."



"Drinking Coke."



"Princess with a castle in the background."



"Eating a watermelon."



Figure 8. More results by CreativeSynth.

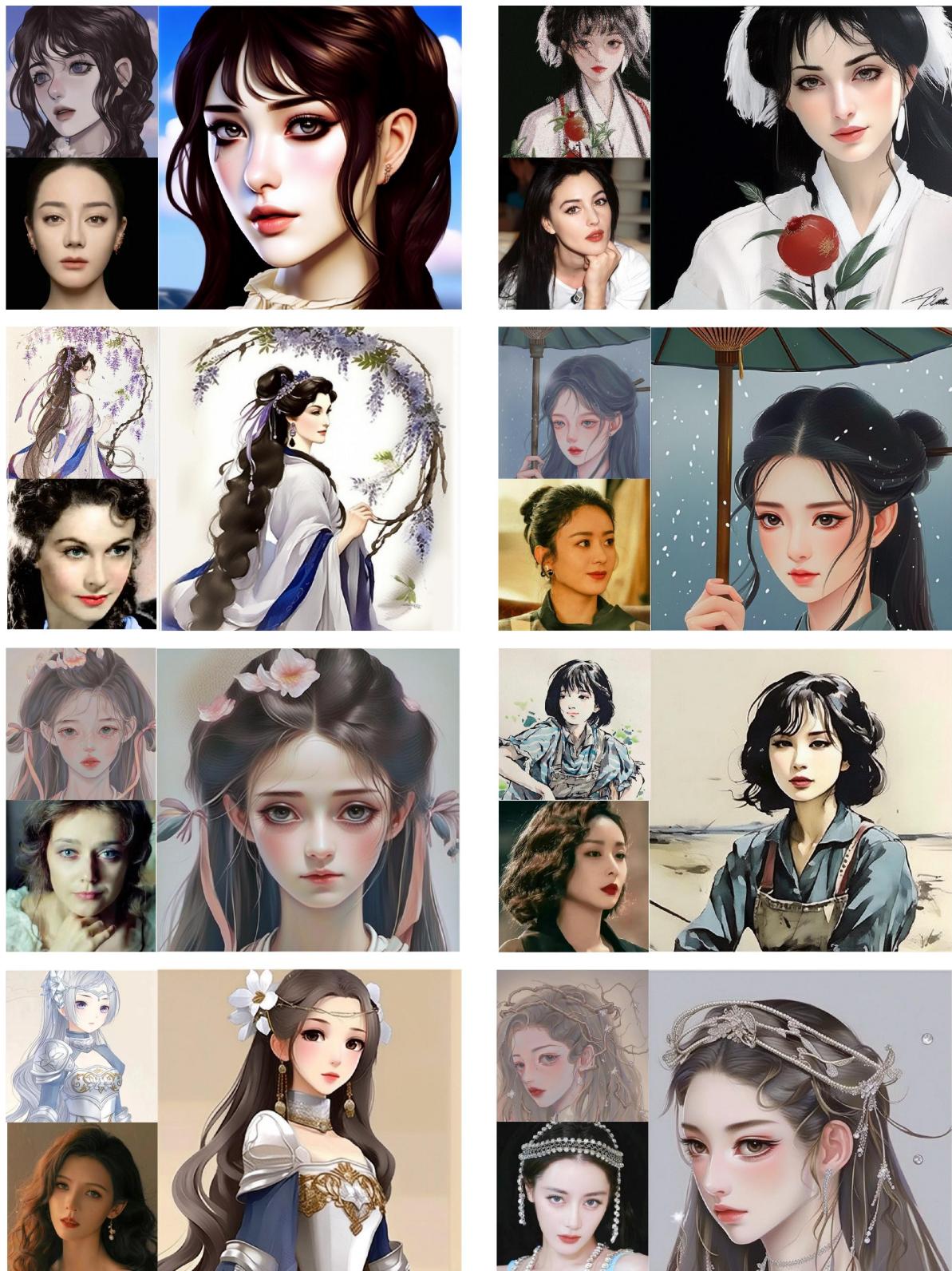


Figure 9. More results by CreativeSynth.

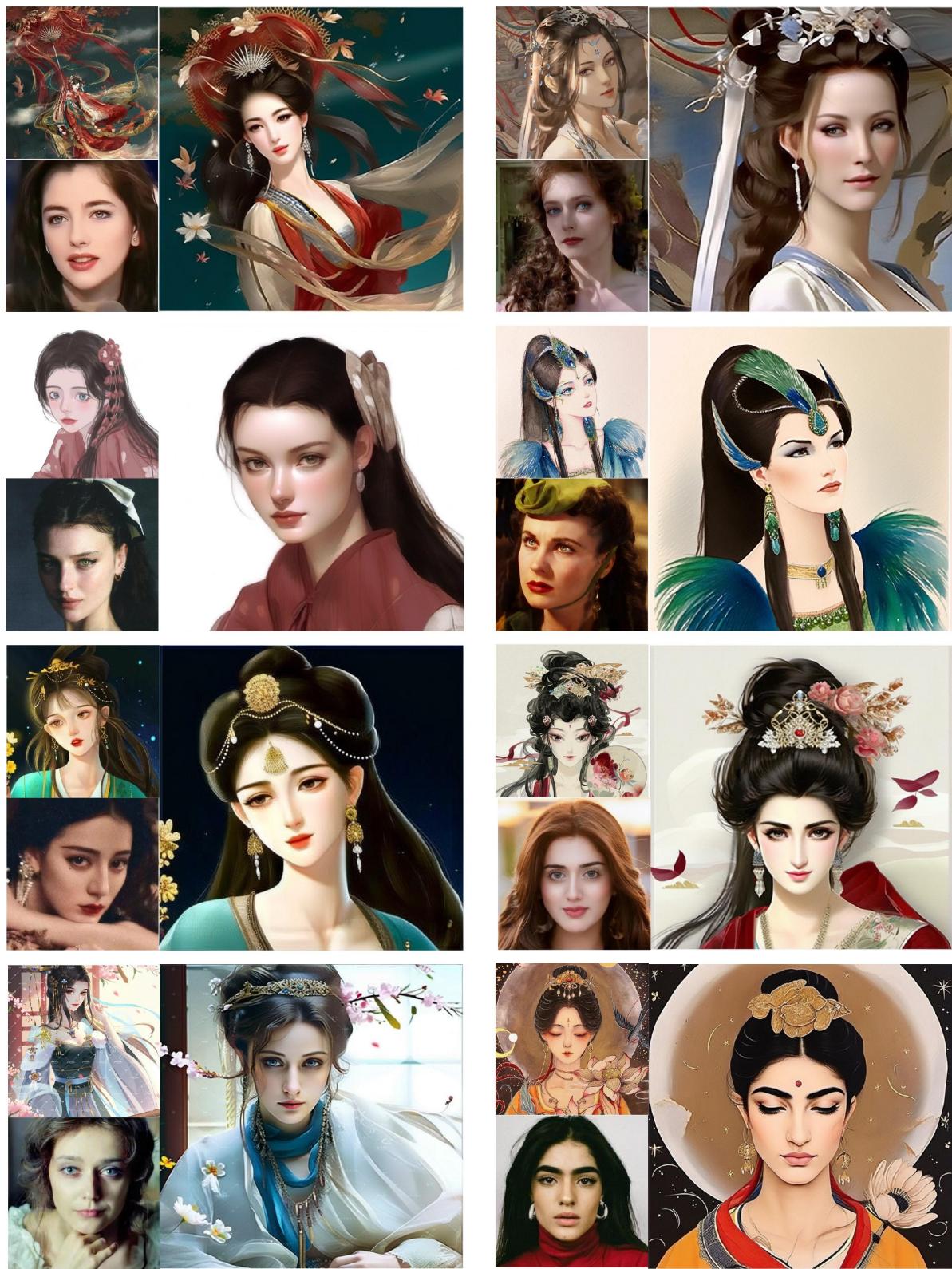


Figure 10. More results by CreativeSynth.

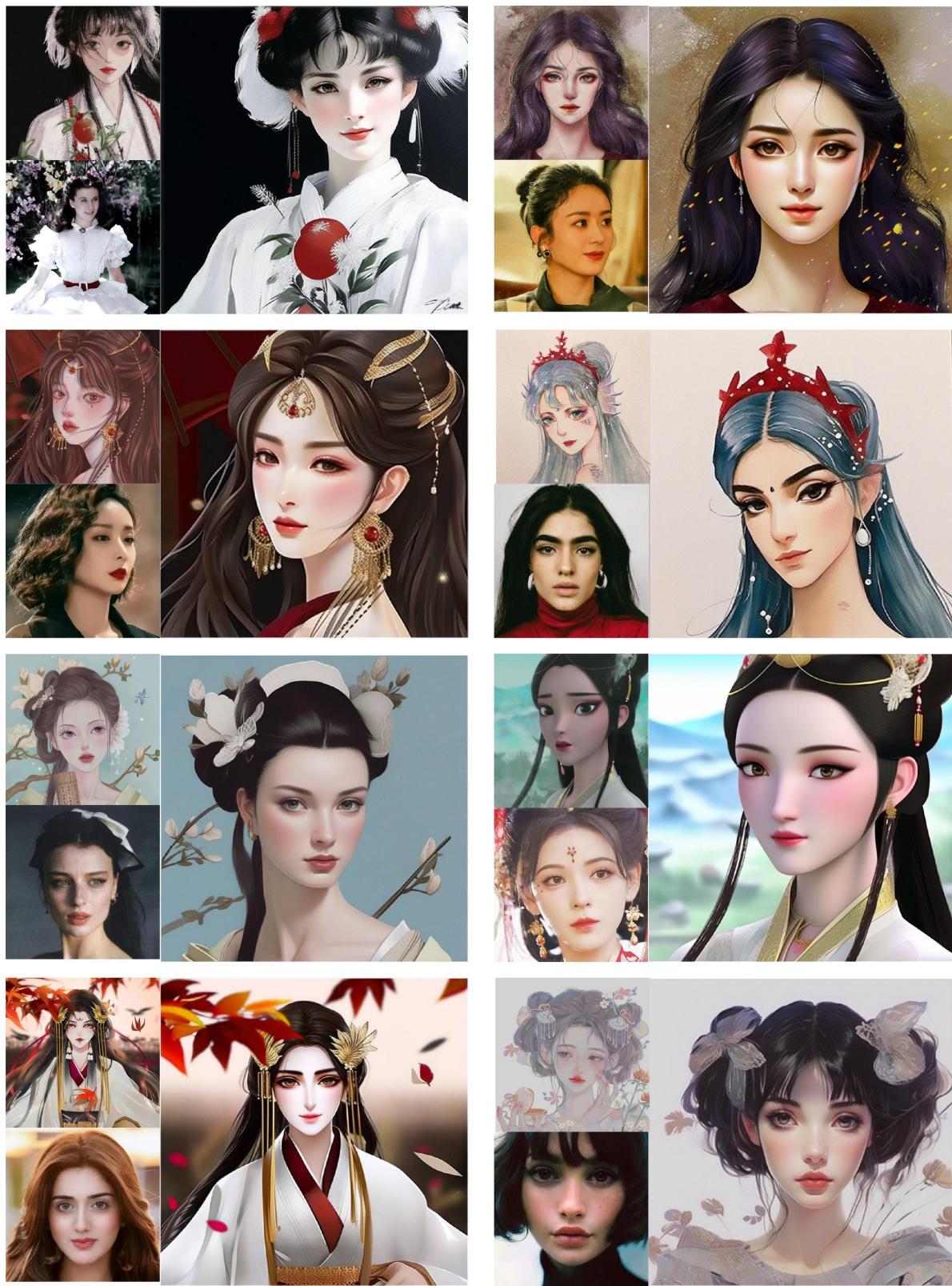


Figure 11. More results by CreativeSynth.

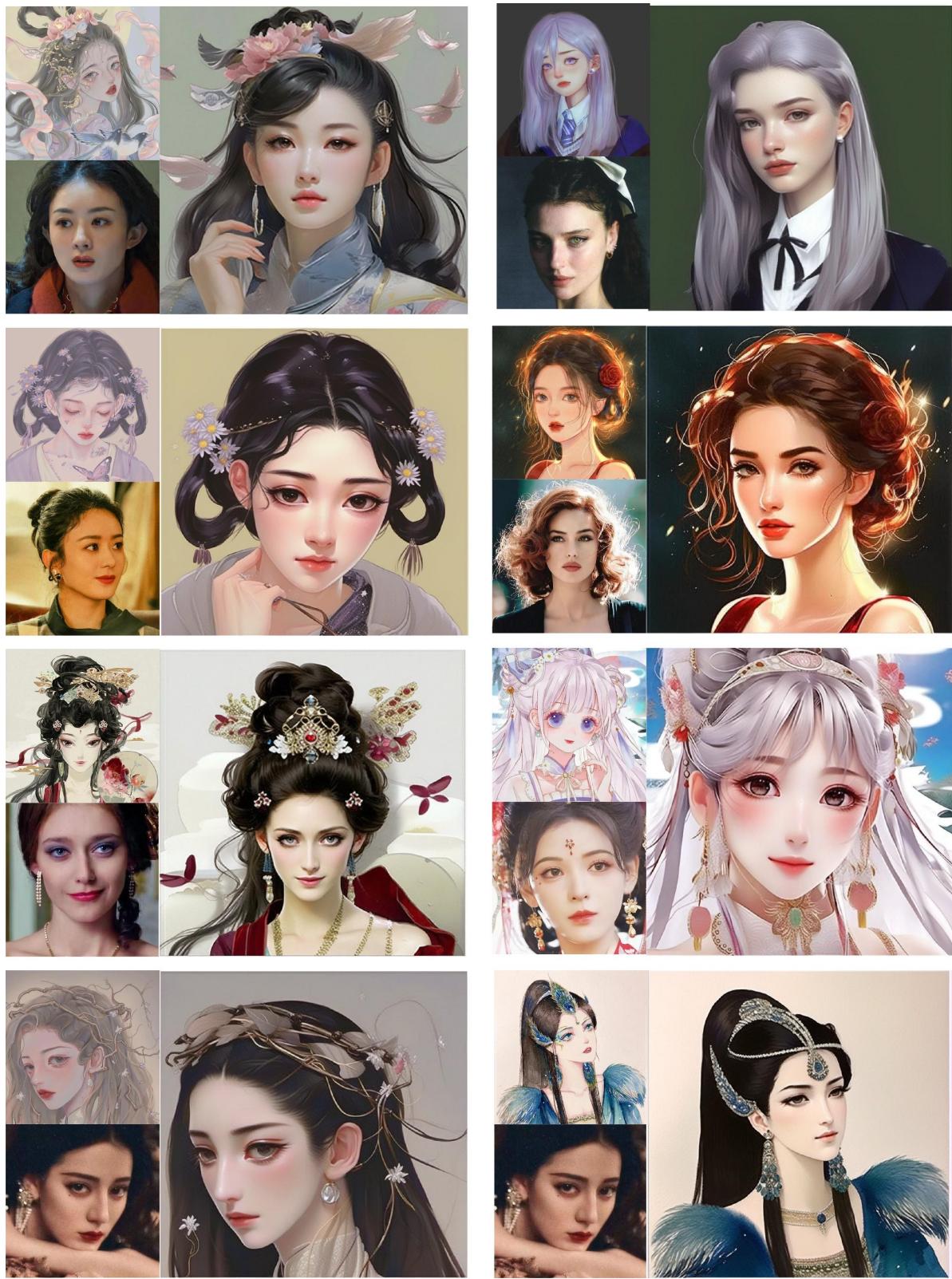


Figure 12. More results by CreativeSynth.

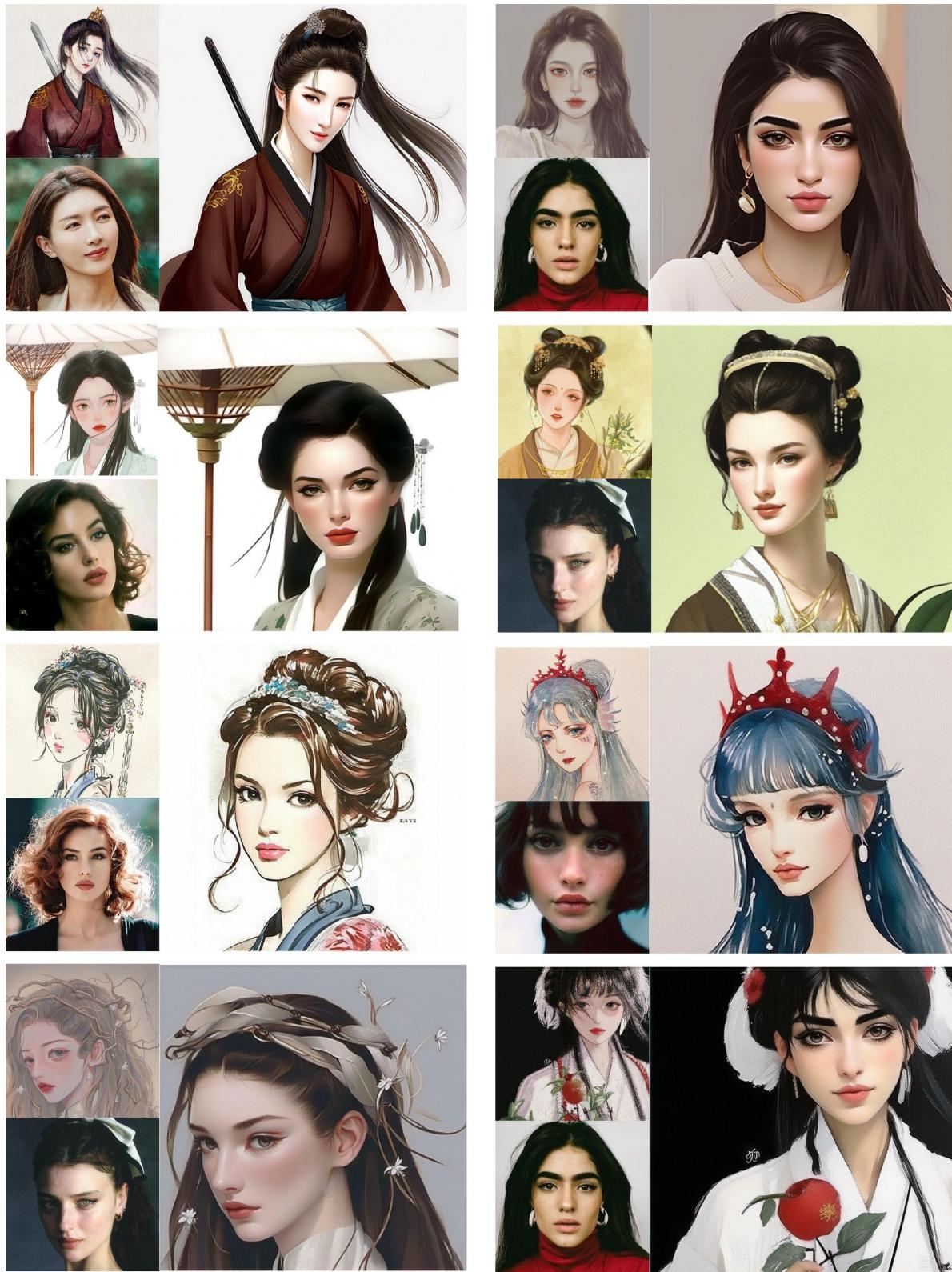


Figure 13. More results by CreativeSynth.

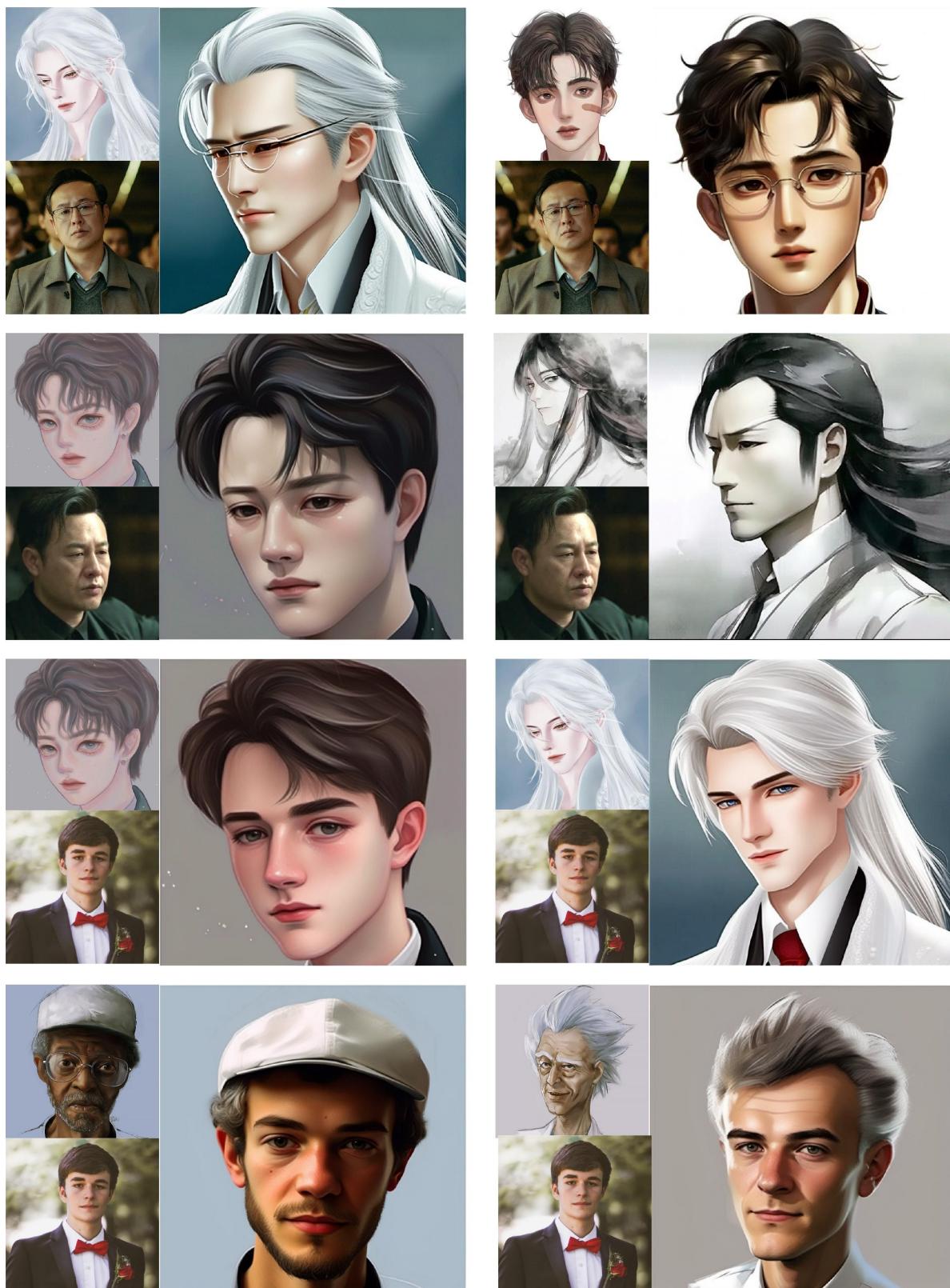


Figure 14. More results by CreativeSynth.

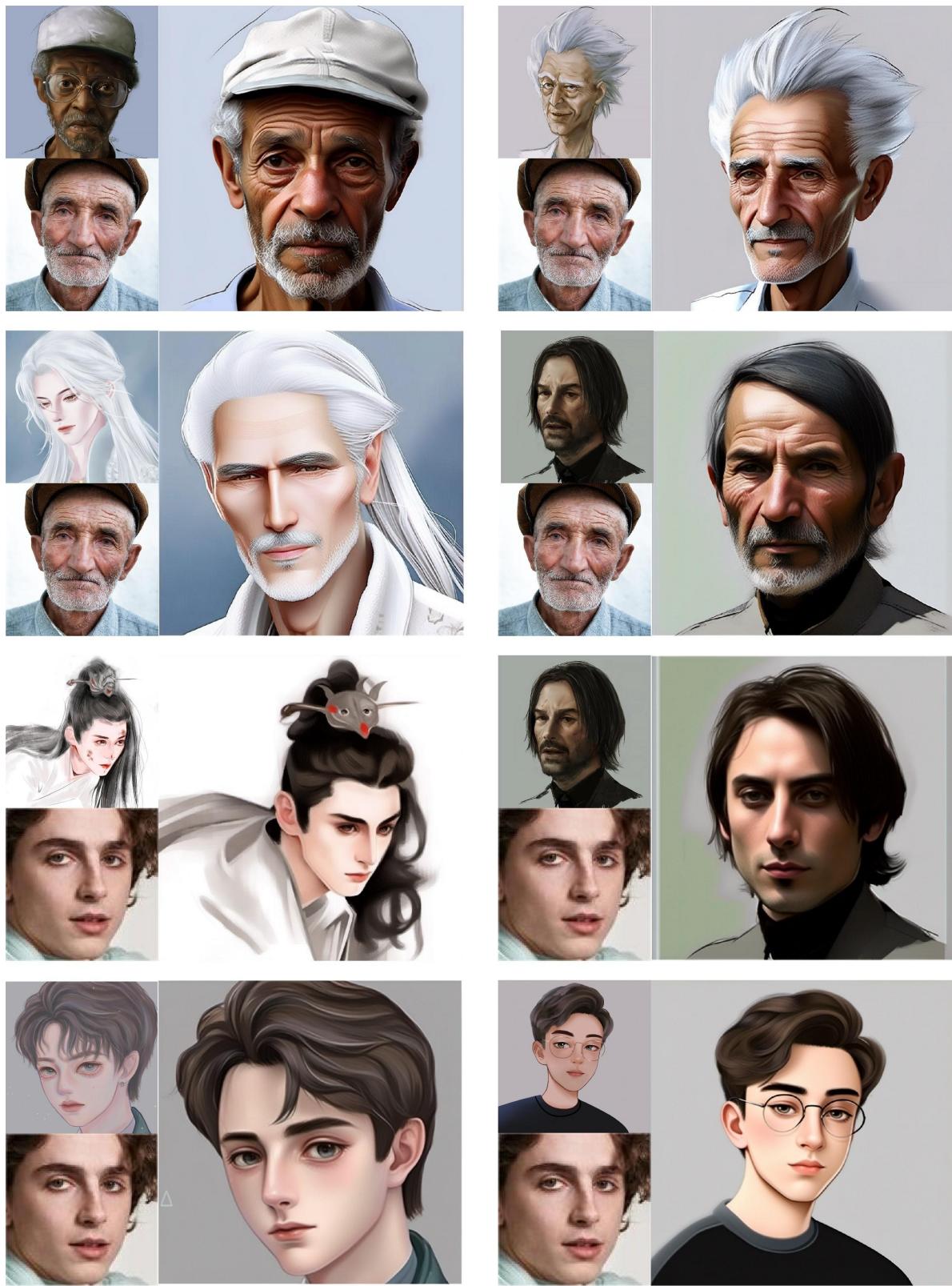


Figure 15. More results by CreativeSynth.



Figure 16. More results by CreativeSynth.

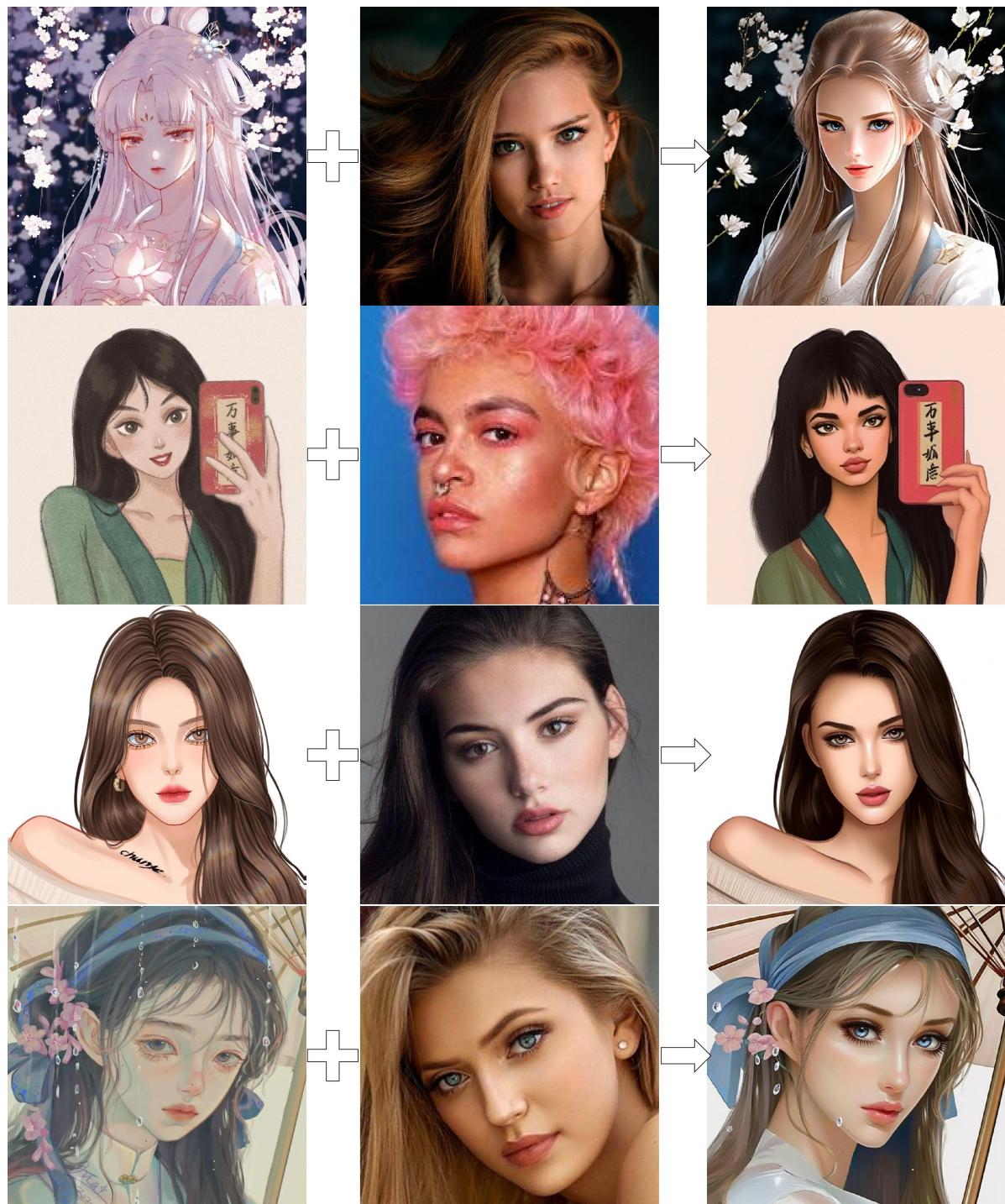


Figure 17. More results by CreativeSynth.

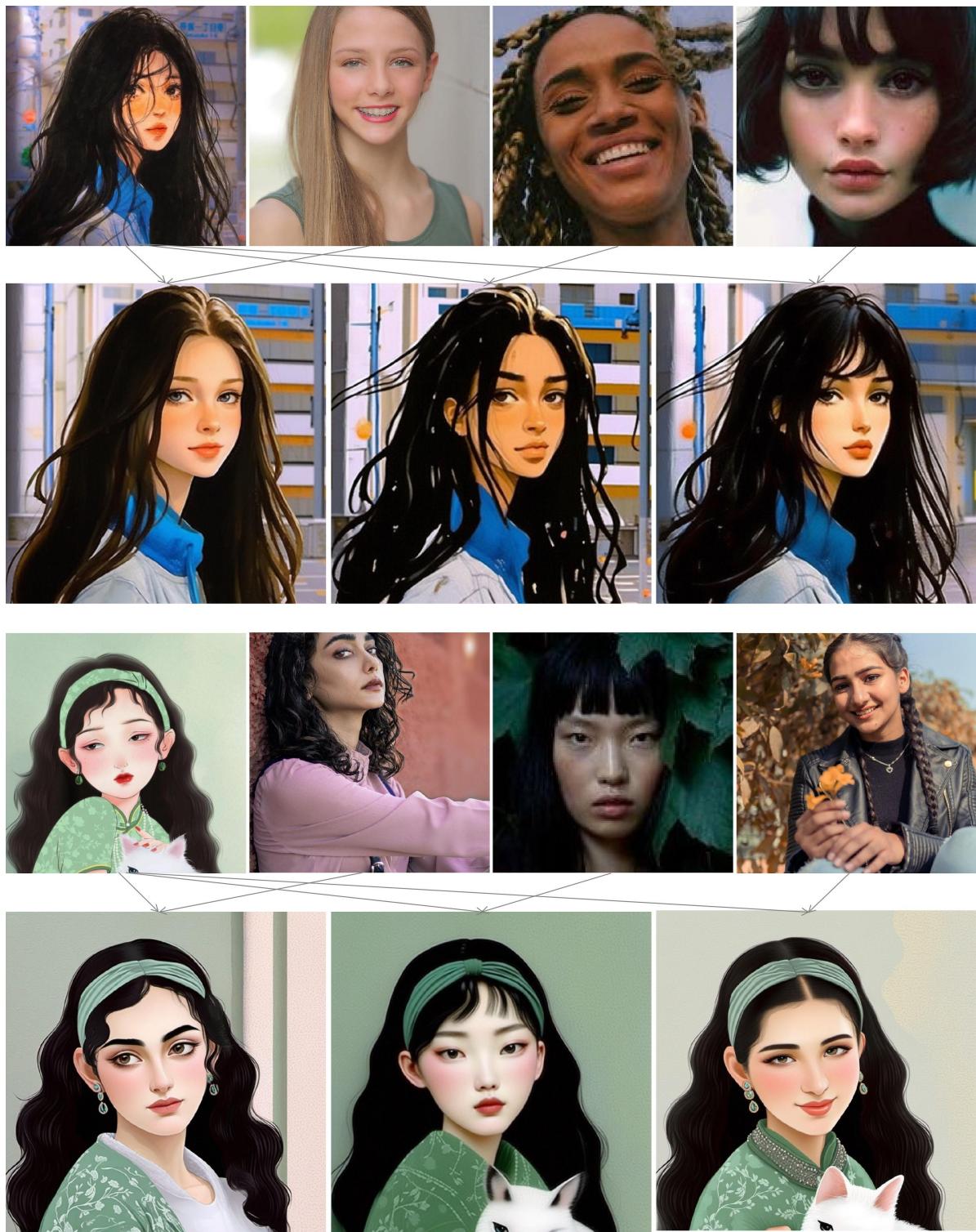


Figure 18. More results by CreativeSynth.

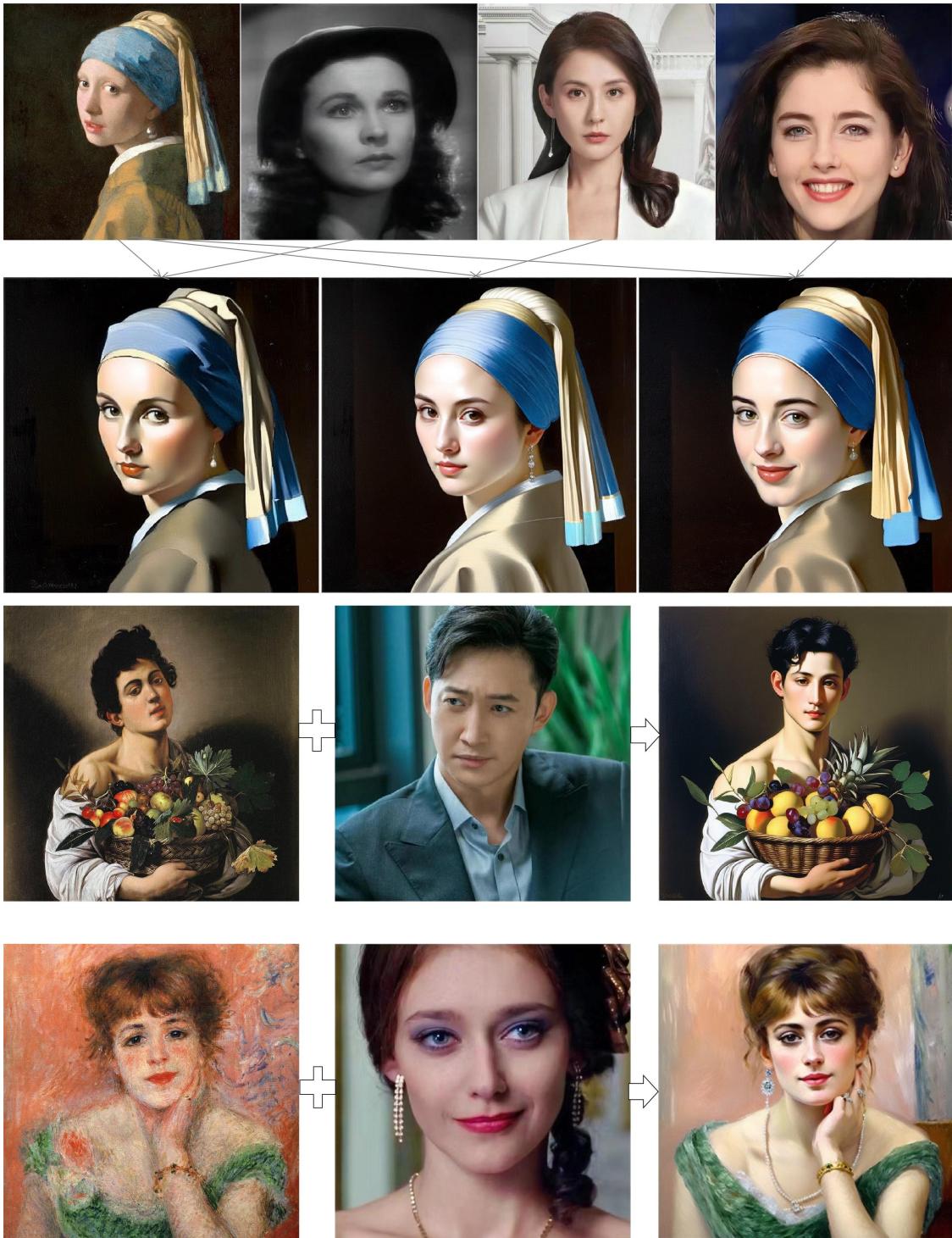


Figure 19. More results by CreativeSynth.